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Assessing the Performance of Demand-Side Strategies and Renewables; Cost and Energy Implications for the Residential Sector

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Assessing the Performance of Demand-Side Strategies and Renewables; Cost and Energy Implications for the Residential Sector

by

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Dedication

I would like to dedicate this dissertation to my loving parents, El Hachmia Frichiche and Abderrahmane Bouhou whose words of encouragement and prayers have carried me through this experience and pushed me for tenacity. I also dedicate this work to my sisters, Kawtar, Oumaima, and Hiba whose moral support and abundant love inspired me with confidence and determination.

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Assessing the Performance of Demand-Side Strategies and Renewables; Cost and Energy Implications for the Residential Sector

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Many public and private entities have heavily invested in efficiency measures and renewable sources to generate energy savings and reduce fossil fuel consumption. Private utilities have invested over $4 billion in energy efficiency with 56% of these investments directed towards consumer incentives. However, the magnitude of the expected savings and the effectiveness of the technological measures remain uncertain. Multiple studies attribute the reasons driving these uncertainties to behavioral phenomena such as "the rebound effect." This work provides insights on the uncertainties generating potential differences between expected and observed performances of demand-side measures (DSM) and distributed generation strategies, using mixed methods that employ both empirical analyses and engineering economics. This study also provides guidelines to stakeholders to effectively use the benefits from DSM strategies towards asset preservation for affordable multifamily houses.

Section 2 describes how joint efficiency gains compare to similar singular efficiency gains for single-family households and discusses the implications of these differences. This work provides empirical models of marginal technical change for multiple residential electricity end-uses, including space conditioning technologies, appliances, devices, and electric vehicles. Results indicate that the relative household

level of technological sophistication significantly influences the performance of demand-side measures, particularly the presence of a programmable thermostat. As to space conditioning, results demonstrate that sufficient consistent technical improvement leads to net energy savings, which could be due to technical factors or to a declining marginal rebound effect.

Section 3 empirically evaluates the performance of distributed residential photovoltaic (PV) solar panels and identifies the technological and demographic factors influencing PV performance and adoption choice. Results show that modeling PV adoption choice significantly impacts the household energy demand, suggesting that the differences in the actual evaluated behavioral responses and the self-reported changes in electricity consumption are more complex than assumed by other studies. The analysis indicates that electricity use decreases marginally for PV adopters if sufficient efficiency improvements in space conditioning are made. Results further imply that households that adopt solar panels might "take back" roughly 24% of the annual electricity production for PV technologies.

Section 4 describes replicable engineering economic models for estimating conventional rehabilitation, energy, and water retrofit costs for low-income multi-family housing units. The purpose of this study is to prioritize policy interventions aimed at maintaining property location and use, and to identify the capital investment needs that could be partially provided by local and state housing authorities.

Section 5 synthesizes the work, describes the future work, provides guidelines for local and state efficiency program administrators, and insights on prioritizing and designing efficiency interventions.

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1. Background and Motivation

Nearly 40 quadrillion Btu's of energy use per year are required by energy services demanded from buildings (i.e. lighting, space conditioning, etc.) [DOE, 2008]. Long-term overall growth in the U.S. housing market has increased building energy consumption, which accounts for more than 40% of the U.S. energy use [DOE, 2008]. The U.S. Department of Energy (2008) estimates that building energy consumption accounted for about a third of total U.S. greenhouse gas between 1980 and 2005.

Policies and measures targeting energy demand reductions thrived over the last three decades, in response to growing concerns about the sensitivity of the economies to oil dependence and more recently climate change. Since the early 1980s, many local and state entities have tightened building energy codes and standards to improve residential energy efficiency standards in an attempt to achieve reductions in energy demand [DOE, 2008; Deason et al., 2011]. Beyond building codes for energy use, the U.S. government has fostered the implementation of demand side management strategies to achieve the desired energy reductions and decrease green house gas emissions [Geller et al. 2006; Gillingham et al., 2006; York et al., 2012].

The U.S. Energy Information Administration defines DSM as "the planning, implementing, and monitoring of utility activities designed to encourage consumers to modify patterns of electricity usage." They include energy efficiency, conservation policies, and demand response (DR). Energy efficiency measures (EE) refer to the technologies that deliver more services for the same energy input, or the same services for less energy inputs. In the context of DSM, energy efficiency attempts to decrease the energy consumption of equipment through new technologies or efficient equipment upgrades. Examples of energy efficient technologies and materials include heat pumps, insulation, clothes washers, and lighting fixtures.

Conservation efforts are aimed at altering consumer behavior to use fewer energy services and thus less energy. For example, end-users might choose to adjust their standard thermostat temperature by lowering it in the winter and raising it in the summer, or they may unplug appliances when they are not in use, use fewer appliances, or turn off lights when leaving a room. These measures directly reduce energy use, but are dependent on consumer behavior.

Demand response, on the other hand, is designed to change on-site demand for energy during specific time intervals (i.e. lowering during peak periods) by transmitting changes in prices, load control signals or other incentives to end-users to reflect existing production and delivery costs.

Demand-side management programs accelerated in the early 1990s. U.S. utilities spending on demand-side management (DSM) programs more than tripled from roughly $2.0 billion dollars in 2006 to nearly $7.2 billion dollars in 2013 [NBER 2011; CEE 2012; CEE 2013].

DSM performance has been investigated using "measurement and verification" methods. Questions arose over how effective these programs and building standards have been in reducing electricity consumption and at what cost those consumption reductions have been obtained [NBER, 2011; Haney, 2010]. Previous studies demonstrated that projected savings from improvements in residential energy efficiency codes were not fully achieved, primarily due to demographic factors. [Metcalf et al., 1999]. Figure 1 compares observed residential energy consumption to projected energy use resulting from improvements in the leading national residential energy efficiency code from 1975 to 2012.

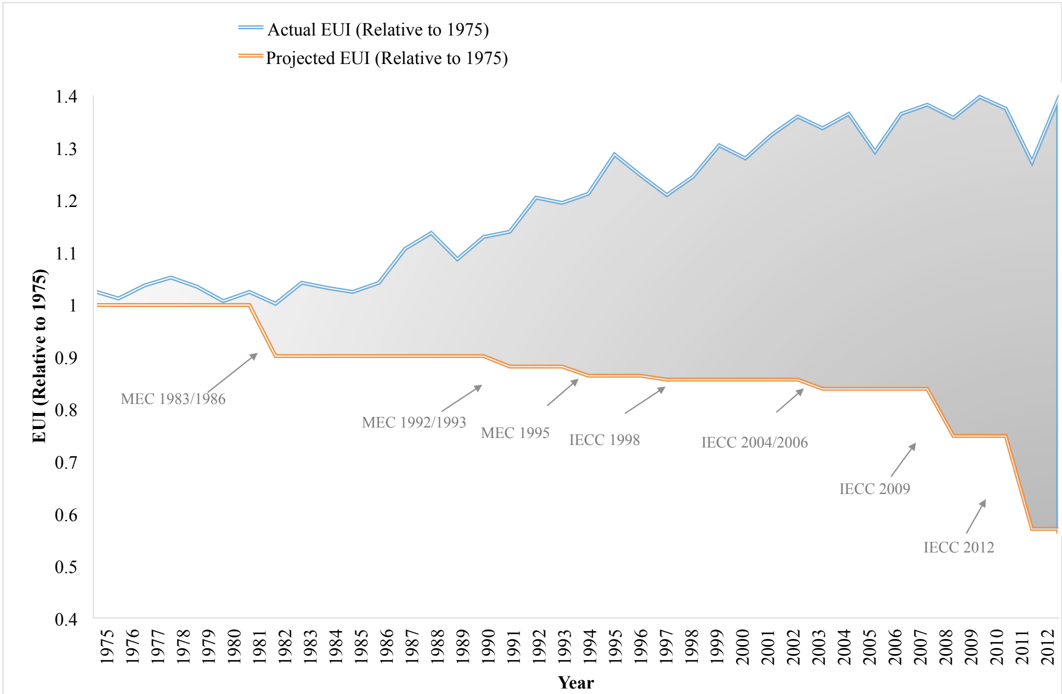


Figure 1: Historical residential actual and projected Energy Use Index (EUI) in the United States (for 1975, EUI=100%). The grey area represents the energy gap between the projected consumption, from building codes improvements, and actual residential energy consumption (*Source: U.S. DOE and U.S. Census*).

Further analysis of implemented residential building codes in the continental United States on electricity consumption, per capita, indicates that although part of the energy gap (gray area in Figure 1) could be explained by the demographic growth, the observed energy use exceeds the engineering estimates (see Figure 2).

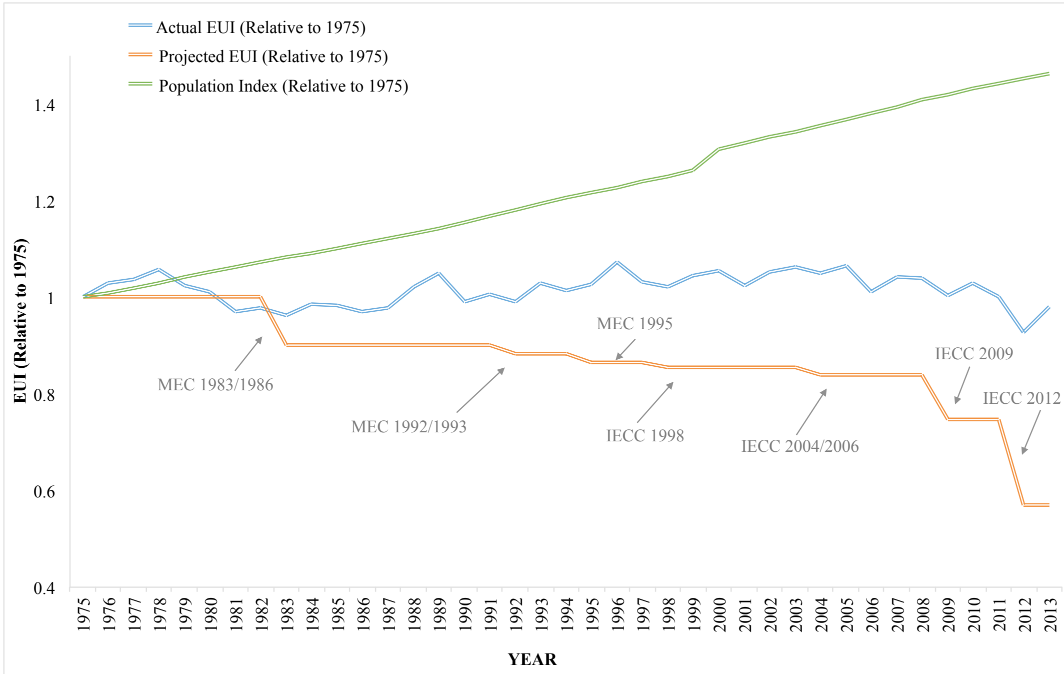


Figure 2: Evolution of the U.S. population, projected, and actual energy use index per capita in the residential sector (for 1975, EUI=100%). (Source: *U.S. DOE and U.S. Census*).

Estimated energy savings are subject to varying degrees of uncertainty, depending on the market conditions [Jaffe et al., 1999; Brown, 2001], the ability of program evaluators to account for organizational and behavioral barriers [Sorrell, 2004], and potential technological deficiencies.

This work better describes the uncertainties underlying performance of demand-side strategies and renewables. Possible sources of uncertainties include the current and future amount and cost of efficiency and renewable stocks, energy demand placed on the efficient equipment, its performance, and uncertainties regarding technology choices and consumer behavior. Previous studies that attempted to highlight these uncertainties are limited in that they are based on qualitative methodologies or engineering modeling techniques. This research is the first to bridge empirical analysis and engineering economics to address the variability and reduce the uncertainty inherent in the interactions of demand-side technologies and policies. It also provides unique insights on the importance of end-user behavioral drivers in the assessments that inform policy interventions.

The overall purpose of the proposed research is to assess the cost and energy implications of demand-side strategies and renewables, for the residential sector. It aims to answer three major research questions that could drive policy decisions:

Question A: How do joint efficiency gains compare to similar singular efficiency gains and what are the implications of the differences?

Within and across electricity services only, householders have four potential uses of efficiency gains: i) homeowners might use efficiency gains exclusively to displace energy consumption, which would realize all technically feasible energy savings; ii) homeowners can use some efficiency gains towards more use of the more efficient services; iii) homeowners can use some efficiency gains for other existing electricity services; iv) homeowners can use efficiency gains to expand energy services into new end uses. Previous quantitative assessments of these behaviors are generally limited to models of technical change of a single energy service using relatively simplistic demand functions or limited empirical assessments. This study described in Section 2 thus provides a unique opportunity to empirically assess residential energy consumption implications of technical changes for multiple technology adopters.

Question B: How do distributed residential photovoltaic solar panels perform and what technological and demographic factors influence performance?

Few studies assess the post-installation performance of rooftop solar panels, and most of these studies are limited to self-reported information on householders' behavioral responses. The empirical analysis in Section 3 investigates the impact of solar energy generation on electricity demand for multiple efficient technologies adopters. This study also emphasizes the importance of modeling the household's technology choice and controlling for unobserved preferences.

Question C: How could the financial benefits generated from energy efficiency and renewable technologies be best utilized to avoid their erosion and preserve multi-family affordable properties?

Section 4 provides an engineering economic model of rehabilitation and energy and water retrofitting costs for affordable multifamily rental housing units located in Austin, TX. The purpose of this work is to identify the capital investment needs that could be partially provided by local housing authorities in order to maintain the property location and affordability for low-income families.

Section 5 summarizes the research and provides recommendations to local and state authorities, based on the work results and policy implications. Section 5 also provides insights on potential future work that should be pursued to further inform policy decisions on best implementation strategies of Demand-Side Management and renewables technologies.

2. An Empirical Analysis of Joint Residential Electricity Efficiency Gains Within and Across End Uses; Implications for Demand-Side Management

Policymakers and researchers have emphasized demand-side strategies to reduce consumption of non-renewable energy sources [NRC 2009; EPA 2008]. As a result, efficiency improvements have become central to energy and environmental policy decisions. DSIRE (2013) reports over 1,400 U.S. programs that provide financial incentives for efficient technology adoption, administered at all levels of government. Spending on demand-side management has also increased. Incentives for electricity demand-side efficiency more than doubled from \$1.9B to \$4.2B from 2005 to 2010 [EIA 2013], and the Federal government invested \$11B in efficiency as part of the American Recovery and Reinvestment Act of 2009 [DOE 2009].

Engineering (or technical) assessments used to inform policy interventions assume an increase in technical operating efficiency leads to an equivalent decrease in energy use (ΔEfficiency = -ΔEnergy). [for examples see NRC 2009; EPA 2008; Creyts et al. 2007; Blackhurst et al. 2010]. To calculate the technically feasible energy savings in a given service area, engineering approaches couple a (i) ranked and ordered estimate of the levelized cost of energy saved by discrete efficiency measures with (ii) an estimate of stock of equipment capable of being replaced or retrofitted. Such assessments are often presented as "conservation supply curves" in the literature. [see examples in NRC 2009; Azevedo 2009].

Engineering assessments disregard behavioral responses to technical change. Increased efficiency decreases the implicit cost of energy services, and consumers respond by increasing quantity demanded. This behavioral response is often called the "rebound effect," "Jevon's paradox," or the "energy efficiency paradox" and is often cast as "eroding" some or all of the technically feasible savings. Residential rebound effects are often separated into direct and indirect effects. The direct effect is confined to a single end-use, referring to the increase in energy service following an efficiency improvement or the elasticity of an energy service with respect to its own efficiency change. Equation 1 shows a typical derivation of direct rebound using the definition of technical efficiency [Berkhout et al. 2000].

$$E = S/\varepsilon \ \rightarrow (\partial E/E)/\,(\partial \varepsilon/\varepsilon) = \eta_{\varepsilon}(E) = \eta_{\varepsilon}(S) - 1 \qquad \textbf{Equation 1}$$

where E = Input Energy; S = Service or Output Energy; ε = efficiency; η denotes elasticity

Equation 1 indicates that the direct rebound effect, $\eta_{\varepsilon}(S)$, is the elasticity of an energy service with respect to its own technical efficiency. If $\eta_{\varepsilon}(S) = 0$, Equation 1 simplifies to a purely engineering assessment, or ΔEfficiency = -ΔEnergy. As a result, direct rebound is often attributed to the behavior that "takes back" efficiency gains for additional energy services. Classic examples of the "take back" effect include consumers driving more with more fuel efficient vehicles [Greene 2012] and consumers altering thermostat setting for additional thermal comfort in response to increased building shell efficiency [Schwartz and Taylor 1995].

Indirect rebound is driven by re-spending on other goods and services. Respective energy consumption is attributed to the energy required by the productive sectors to meet the demands of such re-spending (or the energy "embodied" in the goods and services associated with such re-spending) [Thomas and Azevedo 2013; Freire-Gonzales 2011]. Significantly less theoretical and empirical research has been conducted on indirect rebound effects.

The existing literature and models of rebound assume discrete technical change for a single energy service, such as replacing a single appliance or adding insulation to a home. However, households experience consistent and correlated exogenous (e.g., Federal standards) and endogenous efficiency change (e.g., voluntary adoptions). The average U.S. household has three efficient technologies installed; 10% have five or more; and 80% two or more technologies [EIA 2013]. These data suggest that many households make consistent (or correlated) efficiency choices. Correlated efficiency changes across end uses challenge the "single service" paradigm that dominates the literature. Limited research has been done on how this observed consistent marginal efficiency change affects rebound. Binswanger (2001) uses indifference curves to qualitatively demonstrate the importance of the income effect for rebound outcomes, emphasizing that indirect rebound may be larger for energy intensive substitutes. The reduction in the cost of energy services induced by increased technical efficiency increases real income, which increases the quantity demanded for a normal good (the income effect). For households, energy intensive substitutes involve equipment and technologies with efficiency performances dictated by homeowners. The importance of income effects is also emphasized by more recent research by Saunders (2013). Blackhurst and Ghosh (2014) use a Solow production function to develop an energy use elasticity model that includes two energy services with distinct but simultaneous efficiency changes. Results show that correlated but disproportionate efficiency change can significantly affect rebound outcomes.

The literature demonstrates mixed models of and insights into the behavioral drivers of energy technology choice and use. Neoclassical models assume consumers maximize utility given an income constraint; however, empirical estimates of the implicit discount rate for efficient technology adoptions indicate consumers generally do not behave this way with respect to efficiency [Hausman 1979; Sanstad et al. 1995]. Richer, more nuanced underlying behaviors could broadly be described as driven by demographics [Hatman 1988; Michelson and Madner 2012], underlying environmental valuation [Cummings and Taylor 1999; Hanley et al. 1990; Bateman et al. 2011], technological awareness [Nair et al. 2010; Attari et al. 2010], or satisficing [Dennis 2006]. Behaviors could also be affected by efforts to promote efficiency that are exogenous to households, such as the EnergyStar program [DOE 2013], the EnergyGuide labels [FTC 2013], and the incentives typical support technology adoption [DSIRE 2013].

Despite the above qualitative insights highlighting uncertain behavioral drivers of technology choice and energy consumption, existing studies suggest the direct rebound can be approximated by the price elasticity of energy services [Sorrell 2007; Greene 2012]. This relationship seems intuitive and, with a few simplifying assumptions, can be derived mathematically from Equation 1 [see Sorrell 2007]. However, the literature summarized above qualitatively challenges such a simplified empirical measure of rebound, which essentially treats as homogenous both the behavioral reactions to technical change and the relative effect of technical change on energy services.

The literature speaks to a broader question: do homeowners correlate or compensate underlying valuations and respective behaviors with respect to energy technology choice and use? Within end uses, previous research has demonstrated a spirited debate about the degree to which consumer satiation (or utility saturation) may be reached with "enough" efficiency change [Lovins 1998; Binswanger 2001; Madlener and Alcott 2009]. Across end-uses, income and substitution effects are expected to be important for energy intensive services but are empirically uncertain [Binswanger 2001; Saunders 2013; Madlener and Alcott 2009].

While drivers of technology choice are likely important determinants for rebound, behaviors during use may have a more significant impact on net energy consumption given the residential sector accounts for more than 20% of primary energy use [EIA 2014]. Within this analysis, four alternatives for householder uses of efficiency gains within and across electricity services are condidered. First, homeowners can use efficiency gains exclusively to displace energy consumption, which would realize all technically feasible energy savings. Second, homeowners can use some efficiency gains for direct rebound, i.e., more use of the more efficient services. Third, homeowners can use some efficiency gains for other existing electricity services, i.e., indirect rebound into existing electricity services (income and substitution effects). Fourth, homeowners can use efficiency gains to expand energy services into new end uses (also income and substitution effects).

This study thus provides a unique opportunity to empirically assess the electricity consumption (and thus rebound) implications of marginal efficiency change within and across end uses. We emphasize that we have only observations of technology choices and consumption (e.g., revealed preferences); we do not have cognitive or ethnographic responses detailing homeowner behaviors (e.g., stated preferences). We do not attempt to quantify the magnitude of potential rebound effects observed in our study sample. We aim to show that behavioral responses are much more nuanced than assumed in most previous studies and determine if indirect rebound across energy services does or does not appear.

2.1. The Pecan Street Dataset

The data used in this study were obtained from the Pecan Street Research Institute (PS). PS is a 501(3)c non-profit that has partnered with The University of Texas at Austin and industry leaders to advance understanding of resource consumption in homes. Pecan Street's core services include collecting, managing, and disseminating high-resolution research data characterizing residential resource consumption and respective determinants. Static data were collected using home energy audits and household surveys. Audit data include nearly 300 fields representing home physical characteristics. Some PS participants have taken extensive annual services characterizing energy and water technology choices, uses, and demographics. Electricity consumption and solar production is monitored at 1-second intervals, which were aggregated to one-month intervals for this study. Consumption data are available for 16 months.

Pecan Street currently has nearly 1,100 participants, mostly located throughout Texas. However, the data collected for each home is typologically inconsistent, and some values are missing. High-resolution, continuous electricity use data are available for about 400 homes. Of those 400 homes, only 120 have been both audited and surveyed. Two surveys are available, which indicated some temporal change in demographic and household factors and technology choices. The exact month of these changes was not reported; thus this work assumes such changes occur at the beginning of the calendar year. Out of these 120 homes, 94 report a zip code, and 19 different zip codes are represented by the sample. Table 1 summarizes our study sample.

Table 1: Summary statistics of the explanatory variables used in the analysis; dummy variables determine whether or not the house has a specific item (e.g. solar panel=1 if the house has a solar panel installed, =0 if not).

Category	**Variable**	**Mean and Standard Deviation (2013 – 2014)**	**Households Reporting Changes from 2013 to 2014**
Climate	Cooling degree days (per month)+	Mean= 261, s = 245	NA

Table1 continued:

Structural factors	Floor area (square feet)	Mean= 1986, s = 703	0
	Windows area (square feet)	Mean= 256, s =114	14
	Age of the house	Mean= 25.7, s = 25.3	NA
Demographic factors	Household members	Mean= 2.64, s = 1.15	13
	Tenure	Mean= 6.32, s = 7.29	7
	Household income	Mean= \$138k, s = \$101k	23
	College degree	Count = 32	8
	Post-graduate degree	Count = 85	6
Self-reported behaviors	Thermostat setting (degrees F)	Mean= 73.4, s = 4.33	0
	TV hours watched per month	Mean= 145, s = 106	54
	Dishwasher loads per month	Mean= 12, s = 8.28	0
	Clothes washer loads per month	Mean= 16.6, s = 8.79	0
	Hours per month worked from home	Mean= 103, s = 54.9	0

Table1 continued:

Technology choices	Insulation R value	Mean= 29.8, s = 10.9	14
	AC Energy Efficiency Ratio	Mean= 11, s = 1.61	13
	Number of devices++	Mean = 8.17, s =4.75	42
	Multi-pane windows	Count = 86	3
	Energy star refrigerator	Count = 25	1
	Energy star dishwasher	Count = 34	5
	Energy star clothes washer	Count =34	14
		Count = 75	
	Solar panels	Count =34	21
	Electric vehicle	Count=108	4
	Programmable thermostat		
Energy	Electricity consumption (KWh/month)	Mean= 887, s = 613	
+ For any given month, cooling degree days are assumed constant across households as they are all located in Austin, TX [National Weather Service, 2013]. ++ Devices include computers, TVs, tablets, cable or satellite boxes, DVRs/DVD/VCR/BluRay, Stereo systems, and gaming systems			

2.2. Model Specification

We use a mixed effects model to account for repeated measures with both fixed (e.g., floors space) and random effects. The household effect on consumption is assumed to be random, i.e., it treats the intercept in the regression equation as random. This approach treats our sample as randomly drawn from a larger population of households so that results can be interpreted as applicable to this broader population. We use a household identifier randomly assigned by PS as the random effect variable. Similar applications of mixed effects models to residential energy technology choice include Attari et al. (2010) and Revelt and Train (1998).

The Intraclass Correlation Coefficient (ICC), here defined as ICC = $\sigma^2_{households}$ / $(\sigma^2_{households} + \sigma^2_{residuals})$, represents the proportion of total variation in consumption explained by the variance between the households. The term $\sigma^2_{(households)}$ represents the variability between houses, and $\sigma^2_{(residuals)}$ the variability within houses. The ICC provides a diagnostic that characterizes the appropriateness of the mixed model approach. Using a "reduced mixed model" that predicts electricity consumption as a function of only the random household identifier, the ICC is estimated to be 54%, which means that a significant portion of variation in electricity consumption is explained by random variation in the households. As a result, treating the household as a fixed effect could lead to misleading results and randomizing the households (a mixed effects model) is thus a more robust approach. Additional details of the ICC estimation are provided in Appendix A.

The general mixed model specification is shown in Equation 2.

$$\log(Y_{it}) = \beta_0 + \beta_1 CDD_t + \sum_{j=2}^{k} \beta_j S_{ij}^{\alpha} + \sum_{j=k+1}^{m} \beta_j D_{ij}^{\theta} + \sum_{j=m+1}^{n} \beta_j B_{ij}^{\delta} + \sum_{j=n+1}^{p} \beta_j T_{ij} + T_{iz} * T_{ix\,(x \neq z)} + R_i + \varepsilon_{it}$$

Equation 2

Where:

Y_{it} is monthly electricity consumption in KWh, including grid plus consumed on-site generation

CDD_t represents the cooling degree days (they are assumed constant across households as they are all located in Austin, TX)

β_j (j from 0 to 1) are the coefficient estimates for fixed effect

S_{ij}^{α} is a series of household structural factors raised to the power α

D_{ij}^{θ} is a series of household demographic factors, raised to the power θ

B_{ij}^{δ} is a series of household self-reported behavioral factors, raised to the power δ

T_{ij} is a series of technology choices

R_i represents Households' specific effects

ε_{it} represents the error terms

Table 2: Variable types and respective predictors available for model specification and testing.

Variable Type	**Predictors available**
Structural factors, S	Floor space, window area, age of home (from 2013)
Demographic factors, D	Occupancy, income, education, tenure
Behavioral factors, B	Hours working from home, hours watching TV, dishwasher loads, clothes washer loads, thermostat setting
Technology installations, T	Insulation R-value, air conditioning energy efficient ratio (EER), solar panels, programmable thermostat, multi-pane windows, electric vehicles, Energy Star clothes washer, Energy Star dishwasher, Energy Star refrigerator, number of devices (computers, TVs, tablets, cable or satellite boxes, DVRs/DVD/VCR/BluRay, Stereo systems, gaming systems)

Table 2 summarizes up to 25 variables available for model specification and testing. Our sample size limits the number of parameters that can be included in any given model. While the total sample is 120, missing values for selected predictors can shrink the sample to 88 houses. Thus, we limit our models to eight predictors (the informal rule often applied is one independent variable for every ten records). We thus first applied general linear model (GLM) to screen predictors. The General Linear Model (GLM) process is a preliminary step to select the predictor variables that explain the most variability in the outcome. GLM discretely tests the variation explained by each predictor (i.e. Y = f(one predictor)) and is used as a preliminary step to select the variables that explain the most variability in consumption. Using the GLM results, we then specify a final model by modified results from a stepwise procedure combined with applying transformations (shown as λ, α, θ and δ in Equation 2) using BoxCox methods (Box, 1964). Finally, we append the final model with a series of interaction terms (see $T_{iz} * T_{ix\ (x \neq z)}$) in Equation 2) to test the effect of marginal technical change on electricity consumption.

2.3. RESIDENTIAL ELECTRICITY DEMAND MODEL

Table 3 summarizes the General Linear Model (GLM) results and indicates that structural characteristics of the house explain most of the variation in electricity use. The floor and windows area have a high influence in electricity consumption ($R^2_{floorArea}$=0.25, $R^2_{WindSqft}$=0.118). When considered in isolation, number of occupants, several behavioral factors (dishwasher use and temperature set point) and number of devices explain a moderate degree of variability (R^2 ranging from 3-12%).

The GLM results also demonstrate that houses with solar panels consume 42.1% more electricity than households with no solar panels. However, the presence of solar panels does not have a significant effect on electricity consumption (R^2_{solar}=0.0587) even though 63.3% of the houses in the sample have solar panels.

Table 3: General Linear Model (GLM) of the fixed effects for model selection $\log(Y_{it}) = \beta_0 + \beta_1 X_i + R_i + \varepsilon_{it}$ where β_0, β_1 represent the model coefficients, X_i the explanatory variables, R_i represents Households' specific effects and ε_{it} represents the error terms and Y_{it} the response variable (electricity use).

Continuous variables	**Coefficient**	**p-value**	**R^2**	**% change in consumption for 1 unit (or 10%++) increase in X variable**
Cooling degree days (per month)	0.00129	< 0.0001	0.272	0.129%
House Area *(Transformed to $(HouseArea)^{-0.5}$)*	76.3	< 0.0001	0.25	8.42%++
Windows area (in square feet)	0.00197	< 0.0001	0.118	0.198%
Number of devices	0.0415	< .0001	0.117	4.24%
Thermostat setting (in degrees F)	0.0611	< 0.0001	0.109	6.30%
Dishwasher loads per month	0.0225	< 0.0001	0.0923	2.28%
Occupancy	0.0946	0.019	0.0401	9.93%
Age of the house (in years)	-0.00643	0.002	0.0607	-0.641%
Clothes washer loads per month	0.0109	0.057	0.0287	1.09%
Tenure of occupants (in years)	0.0131	0.057	0.00966	1.32%
TV hours watched per month	0.000405	0.115	0.0127	0.0405%
Insulation R value	0.00568	0.123	0.0223	0.57%
Air conditioning EER value	0.0159	0.487	0.00093707	1.60%
Hours per month occupants work from home	0.000398	0.846	0.00775	0.04%
Income	< .0001	0.541	0.0388	< .0001%

Table 3 continued:

Discrete variables				
Solar panels	0.351	0.001	0.0587	42.11%
Programmable thermostat	0.358	0.001	0.0392	43%
Multi-pane windows	0.221	0.027	0.032	24.78%
Electric vehicle	0.0719	0.417	0.00296	7.45%
Education (Bachelors degree)	0.048	0.625	0.000289	4.91%
Energy star clothes washer	0.0361	0.672	0.000137	3.68%
Education (Post bachelors degree)	-0.0201	0.846	0.00127	-1.99%
Energy star refrigerator	-0.0183	0.865	0.000285	-1.81%
Energy star dishwasher	-0.00682	0.955	0.00272	-0.68%
Response variable				
Electricity consumption (KWh/month) *Transformed to logarithm (Electricity use)*	-	-	-	-

We use the GLM results and stepwise regression to screen for predictors to be included in the final mixed models, dropping statistically insignificant predictors and those that negligibly explain variability in consumption. While stepwise procedures cannot be used blindly for mixed models, we experimented with models specified using stepwise regression (i.e. Stepwise approach applied to Multiple Linear Regression) to specify the final model. We include the technology choices of interest independent of the GLM and stepwise screening procedures to address our primary research questions. The final model is shown in Equation 3:

$$\log(Y_{it}) = \beta_0 + \beta_1 CDD_t + \beta_2 (HouseArea_i)^{-0.5} + \beta_3 ProgTherm_i + \beta_4 Insulation\ R_i + \beta_5 ES.Clothes\ washer_i + \beta_6 Devices_i + R_i + \varepsilon_{it}$$

Equation 3

Table 4 shows model results of a mixed regression model without any technology interaction terms. In the final model, two of the four most statistically significant parameters ($p < 0.1$) are home insulation and the number of devices. The regression coefficient estimate for each variable indicates the percentage change in energy demand with a one-unit (or 10%) increase in the variable of interest, keeping all the other variables constant. For example, a 1-day increase in cooling-degree days increases consumption by 0.13%. A one-unit increase in the house insulation R-value decreases the electricity use by 0.6%. Interestingly, the installation of a programmable thermostat and an Energy Star clothes washer are not statistically significant predictors of electricity consumption. The number of devices is significant at the 10% level, where each device increases consumption by 2%; thus one device negates the savings of a one-unit increase in the insulation efficiency.

It should be noted that there is no conventional determination R2 for mixed models. We thus calculate a 'pseudo-R^2' by assessing the correlation between the observed and predicted responses. For the model with no interaction terms (Table 4) this pseudo-R^2 is 0.53. The ICC for the final model (Table 4) is 60%.

Table 4: Regression mixed model for electricity consumption, without technology choice interaction terms

Explanatory variable	**Coefficient estimate**	**p-value**	**% change in consumption for 1 unit (or 10%++) increase in X variable**

Table 4 continued

Constant (bo)	7.88	<0.0001	-
CDD (Cooling Degree Days)	0.00129	<0.0001	0.129%*
$(\text{HouseArea})^{-0.5}$	-71.4	<0.0001	7.88% ++ *
InsulationR	-0.00592	0.035	-0.59%*
Devices	0.0147	0.074	1.49%*
ProgTherm (Programmable Thermostat)	0.0931	0.238	9.75%
ES Clothes washer	0.06	0.324	6.19%

Standard Deviation Table:

Random effect		**Parameters estimate**	**Standard Error**	**95% confidence interval**
Ri= Household ID	Standard deviation (constant)	0.337	0.027	[0.288 ; 0.394]
	Standard deviation (residual)	0.278	0.00566	[0.267; 0.289]

Note: Devices include computers, tablets, televisions cable or satellite boxes, DVRs/DVD/VCR/BluRay, Stereo systems, gaming systems.

* Statistically significant results to 10% level. ES=Energy Star.

2.4. EVALUATING THE IMPACT OF MARGINAL TECHNICAL CHANGE ON ELECTRICITY USE

The model in Table 4 helps evaluate the individual effect of the adoption of various technologies on energy demand; however, we are interested in marginal technical change within and across end uses to characterize potential income and substitution effects, e.g., to observe if consumers might leverage efficiency gains for added energy services with and across an end use. To test this, we append various interaction terms (see $T_{iz} * T_{ix\,(x \neq z)}$) in Equation 2) to better understand how such marginal technical change affects consumption. We applied screening techniques (including stepwise regression and p-value analysis) to all possible combinations of nine technology choices (a total of 36 mixed models) to identify five models with statistically significant interaction terms. These models and significant interaction terms are summarized in Table 5. The remaining models are summarized in the SI.

Table 5: Mixed models with statistically significant technology interactions derived from the generalized model shown in Equation 2. Coefficient estimates in bold are statistically significant to 10% level.

Significant interactions	**Model Specifications**	**Pseudo R^2**
Programmable Thermostat AND Multipane windows	$\widehat{\log(Y_{it})} = \mathbf{7.56} + \mathbf{0.00123}\ CDD_t - \mathbf{67.9}\ HouseArea_i^{-0.5} + \mathbf{0.259}\ ProgTherm_i - \mathbf{0.153}\ Multipane_i + \mathbf{0.0186}\ Devices_i + \mathbf{0.43}\ ProgTherm_i * Multipane_i$	0.558
Programmable Thermostat AND Air Conditioning	$\widehat{\log(Y_{it})} = \mathbf{8.34} + \mathbf{0.00127}\ CDD_t - \mathbf{65.7}\ HouseArea_i^{-0.5} + \mathbf{0.645}\ ProgTherm_i + -\mathbf{0.0699} AC_i + \mathbf{0.016}\ Devices_i + \mathbf{0.0691}\ ProgTherm_i * AC_i$	0.550
Programmable Thermostat AND Energy Star Clothes washer	$\widehat{\log(Y_{it})} = \mathbf{7.47} + \mathbf{0.00127}\ CDD_t - \mathbf{64.8}\ HouseArea_i^{-0.5} + \mathbf{0.18} ProgTherm_i - 0.00183\ ES.CWasher_i + \mathbf{0.0162}\ Devices_i + \mathbf{0.293}\ ProgTherm_i * ES.CWasher_i$	0.544
Energy Star Dishwasher AND Air Conditioning	$\widehat{\log(Y_{it})} = \mathbf{8.16} + \mathbf{0.0013}\ CDD_t - \mathbf{69.5}\ HouseArea_i^{-0.5} + 0.0246\ ProgTherm_i - \mathbf{0.0379}\ AC_i - \mathbf{0.947}\ ES\ DWasher_i + \mathbf{0.0152}\ Devices_i + \mathbf{0.0828}\ AC_i * ES\ DWasher_i$	0.552

Table 5 continued:

Programmable Thermostat AND Electric Vehicles	$\widehat{\log(Y_{it})} = \mathbf{7.61} + \mathbf{0.00129}CDD_t - \mathbf{67.1}\ HouseArea_i^{-0.5} + 0.0833\ ProgTherm_i - 0.0103\ EV_i + \mathbf{0.0174}\ Devices_i + \mathbf{0.754}\ ProgTherm_i * EV_i$	0.546

CDD = Cooling Degree Days
ProgTherm = Programmable Thermostat
AC = Air Conditioning
ES.CWasher = Energy Star Clothes washer
ES.DWasher = Energy Star Dishwasher
EV = Electric Vehicle

Margins plots of fitted values of electricity demands are used to visualize the results and interpret the coefficients of the interaction terms. Each margins plot shows two distinct efficiency improvements: improvements along the x-axis and across the series. Thus each plot shows two situations of positively correlated efficiency improvements. First, values are fitted to marginal improvements shown by increased efficiency along the x-axis (first efficiency improvement) for the more efficient graphed series (second efficiency improvement). As an example, Figure 3 shows fitted values of electricity consumption by increased windows efficiency (first efficiency improvement) in homes with a programmable thermostat (second efficiency improvement). The second source of positively correlated efficiency improvements is shown by fitting values to efficiency improvements across the graphed series (first efficiency improvement) at different, discrete values along the x-axis (second efficiency improvement).

Figure 3 shows two situations where marginal efficiency change leads to rebound. First, homes with a manual thermostat are predicted to “take back” efficiency gains (and increase by 204 kWh/month) from multi-pane windows as shown by the blue line. Second, homeowners with single pane windows “take back” the efficiency gains (an increase of 189 kWh/month) of replacing a manual thermostat with a programmable thermostat (see arrow 1 in Figure 3). Results show net energy reductions are only achieved with "enough" efficiency improvements, including adopting both multi-pane windows and a programmable thermostat (shown by arrow 2 in Figure 3). This is shown schematically in the Venn diagram in Figure 4, where the effect of marginal technical change is dependent on the baseline technical state of the home, where the effect of predicted consumption associated with joint technical change is dependent on the respective baseline condition of discrete technical interventions. These results contrast with those without any interaction terms (see Table 4), which indicated no statistically significant effect for the presence of a programmable thermostat. By controlling for other sources of technical change within air conditioning (here the presence of multi-pane windows), the affect of a thermostat becomes statistically significant.

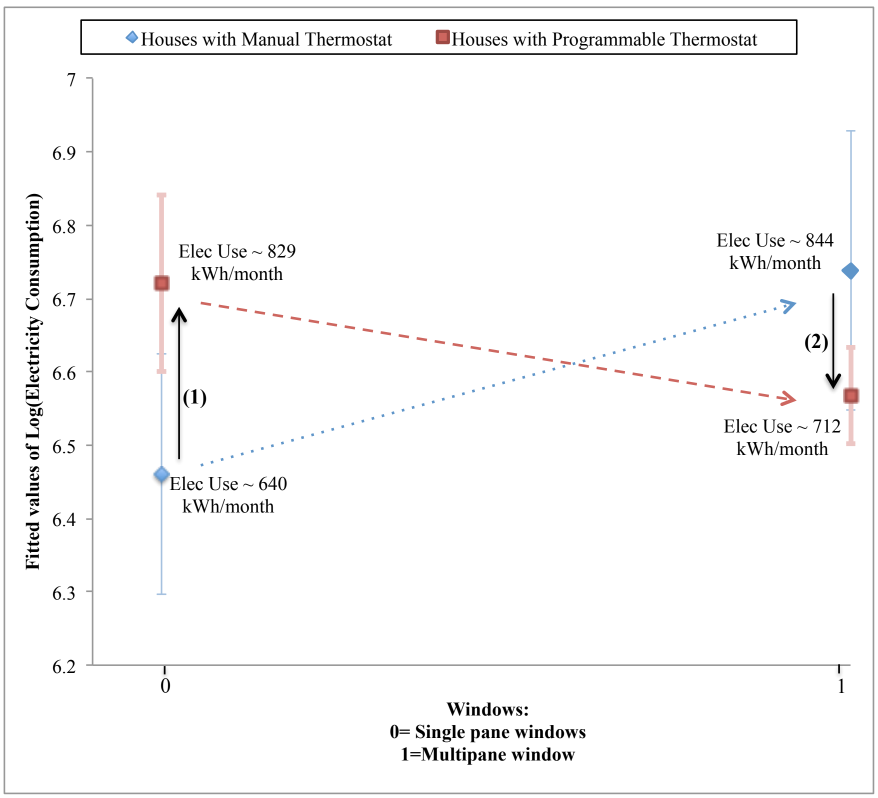


Figure 3: Fitted values of log(electricity consumption) given marginal efficiency changes for multi-pane windows and thermostat type.

The fitted values are given with 90% confidence intervals. Arrow 1 shows houses with single pane windows consume more electricity (ΔElec ~189 kWh/month) if they have a programmable thermostat. Arrow 2 shows houses with multi-pane windows and a programmable thermostat decrease their electricity consumption (ΔElec ~-132 kWh/month).

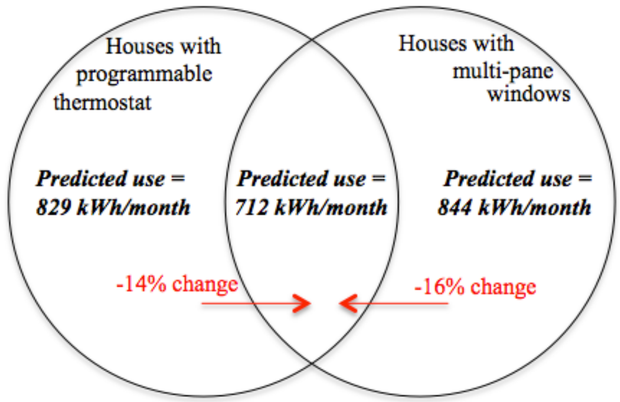


Figure 4: Venn diagram describing the impact of marginal, joint technical change on predicted electricity consumption given two different baseline technical conditions for number of window panes and thermostat type.

We used the fitted values of log(Electricity use) in the respective mixed regression models described in Table 5. Taking the example from the Venn Diagram in Figure 4, these estimates were calculated for two subsets of households: houses with Manual thermostats, and houses with programmable thermostats. The estimates were, then, exponentiated to obtain the kilowatt-hours per months. Table 6 describes the results for the interaction between thermostat performance and windows performance.

Table 6: Fitted values of electricity consumption (in KWh/month) calculated using the interaction between thermostat performance and windows performance.

Houses with Manual Thermostat				**Houses with Programmable Thermostat**			
Windows performance	*Predicted mean of log(Elec Use)*	*(90% Confidence Interval)*		*Windows performance*	*Predicted mean of log(Elec Use)*	*(90% Confidence Interval)*	
		Min	*Max*			*Min*	*Max*
Single pane	640	543	754	Single pane	829	735	935
Multipane	844	698	1020	Multipane	712	666	760

Based on Table 6, the percent difference in electricity use between homes with single pane and those with multi-pane windows and a programmable thermostat is roughly 14%. For houses with multi-pane windows, the percent difference in electricity use between homes with manual and those with programmable thermostats is 16%.

Figure 5 shows fitted consumption for marginal change across end-uses: clothes washers and space conditioning (as designated by the presence of a programmable thermostat). Similar to the trends within space conditioning (Figure 3 and 4), Figure 5 demonstrates two areas of rebound. First, fitted values of consumption for homes that do not have a programmable thermostat demonstrate rebound with the adoption of an Energy Star clothes washer. Households with a manual thermostat are estimated to consume 34% more if they own an EnergyStar clothes washer. Second, slight rebound is predicted in homes with a minimum code clothes washer (value of 0 on x-axis) that install a programmable thermostat. Results again show net energy reductions are only achieved with "enough" consistent efficiency improvements (the adoption of both an Energy Star clothes washer and programmable thermostat). These trends are similar to those observed for marginal technical change within space conditioning (see Figure 3); however, they occur across energy services.

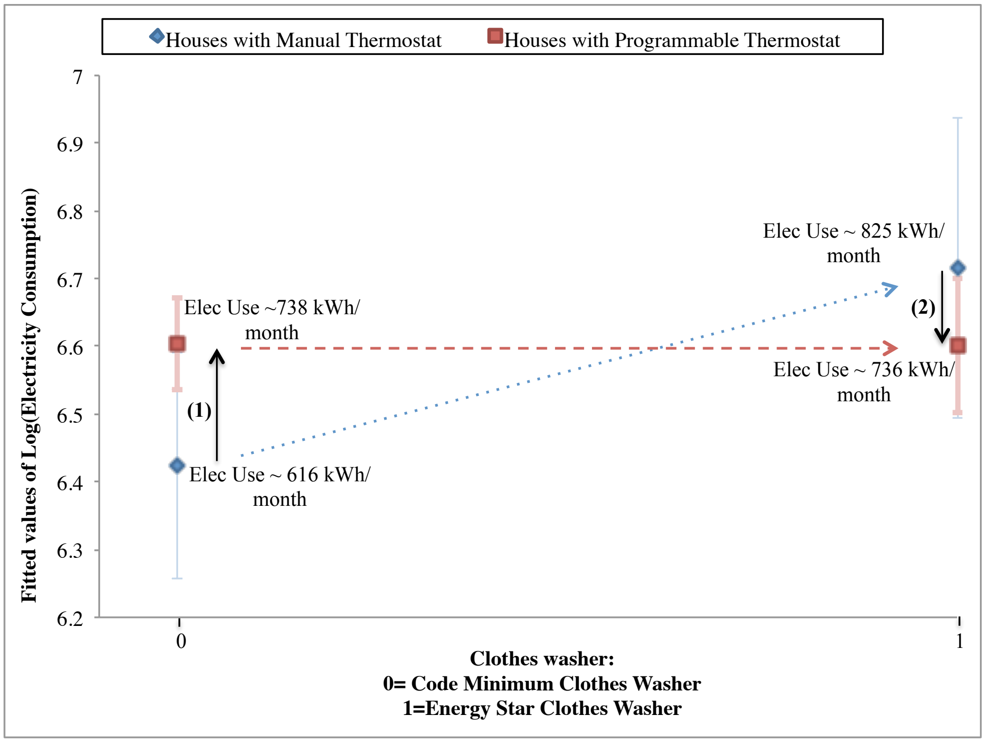


Figure 5: Fitted values of log(electricity consumption) given marginal efficiency changes for clothes washer and thermostat type.

The fitted values are given with 90% confidence intervals. Arrow 1 shows houses with a minimum code clothes washer consume more electricity (ΔElec ~122 kWh/month) if they have a programmable thermostat. Arrow 2 shows houses with Energy Star clothes washer and a programmable thermostat decrease their electricity consumption (ΔElec ~ -89 kWh/month).

By using devices and electric vehicles as proxies for new electricity services, we now consider the potential for householders to utilize space conditioning efficiency gains for energy service expansion. While not statistically significant, Figure 6 indicates that houses with a programmable thermostat are predicted to use more electricity with increasing devices, a trend that is expected. However, homes with a manual thermostat show the number of devices has a near negligible effect on predicted consumption. For homes with the average number of devices (average = ten), homes with a programmable thermostat are expected to consume 19% more electricity than houses with a manual thermostat (see arrow 2 in Figure 6).

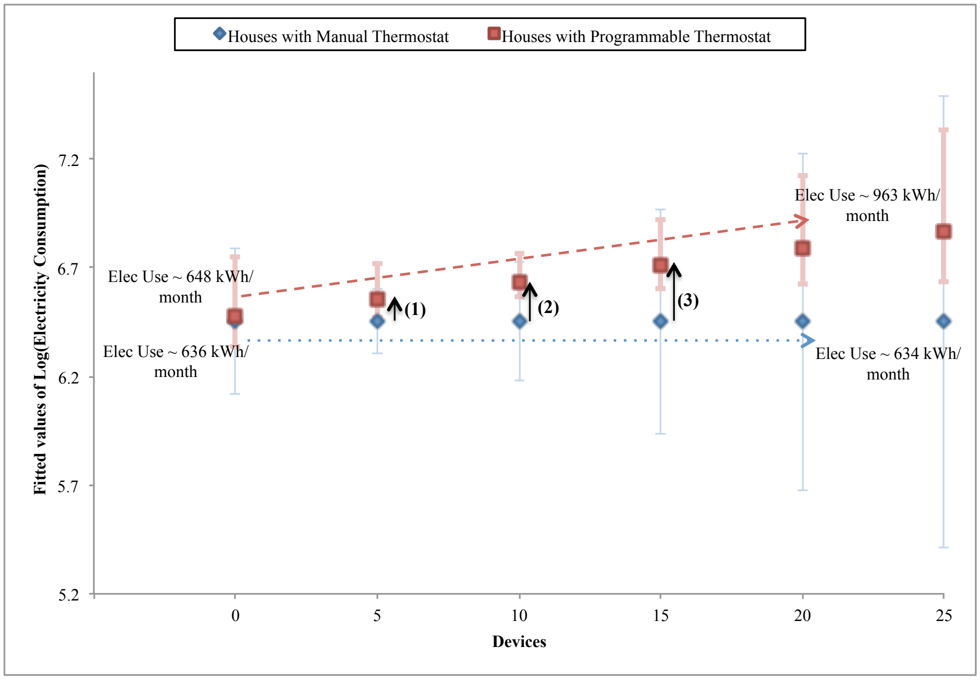


Figure 6: Fitted values of log(electricity consumption) for homes with varying electronic devices and thermostat type.

The fitted values are given with 90% confidence intervals. Devices include computers, tablets, televisions, cable or satellite boxes, video media players, stereo systems, and gaming systems. Arrow 1 shows houses with few devices are predicted to consume more electricity (ΔElec ~66 kWh/month) if they have a programmable thermostat. Arrow 2 shows houses with an average number of devices (~ ten devices) and a programmable thermostat increase their electricity consumption (ΔElec ~124 kWh/month). Arrow 3 shows houses with an above average number of devices (~fifteen devices) and a programmable thermostat increase their electricity consumption (ΔElec ~187 kWh/month).

Figure 7 shows similar interactions between electric vehicles and space conditioning. Fitted values indicate homes with no electric vehicles might slightly rebound when they adopt a programmable thermostat; however a very slight net energy savings is realized in homes with electric vehicles and a programmable thermostat, albeit much smaller absolute amount (as shown in the red line, Figure 7). These trends contrast with those observed for devices.

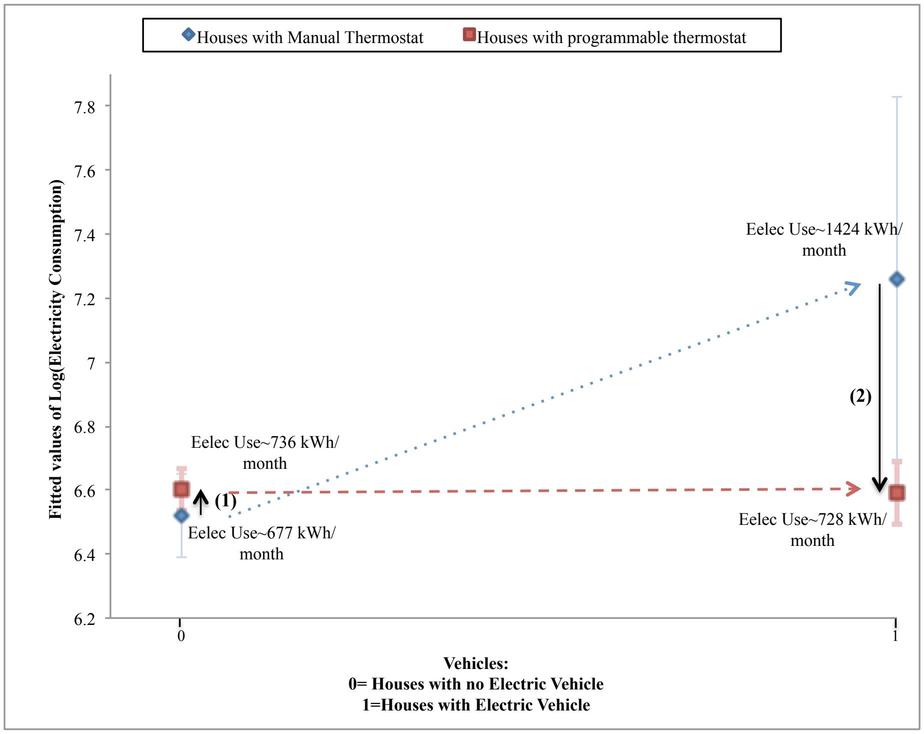


Figure 7: Fitted values of log(electricity consumption) for homes with electric vehicles and thermostat type.

The fitted values are given with 90% confidence intervals. Arrow 1 shows houses with no electric vehicle consume more electricity (ΔElec~59 kWh/month) if they have a programmable thermostat as well. Arrow 2 shows houses with an Electric Vehicle and a programmable thermostat decrease their electricity consumption (ΔElec~ -696 kWh/month).

Figure 8 summarizes increases or decreases in electricity consumptions for nine different sources of marginal technical change predicted using all possible 36 interaction terms. The results above and below the diagonal describe the two distinct sources of marginal technical change presented in Figures 3-7. Consider the example described in Figures 3 and 4. For the subset of households with a programmable thermostat, those without multi-pane windows are predicted to use 829 kWh per month while those with multi-pane windows are predicted to use 712 kWh per month. This net reduction of 14% is shown in the first row of Figure 8, i.e., for all homes with a programmable thermostat (indicated in the first row on Figure 8), homes with multi-pane windows use 14% less electricity. Similarly, Figure 3 indicates that for the subset of homes with multi-pane windows, those with a manual thermostat are predicted to use 844 kWh per month, whereas homes with a programmable thermostat are predicted to use 712 kWh per month. This net reduction of 16% is shown at the top of the first column in Figure 8, i.e., for all homes with multi-pane windows (indicated in the second row), those with a programmable thermostat use 16% less electricity.

		Programmable Thermostat	Multipane Window	Insulation R value R <19	19 <R < 29	R>30	Air Conditioning EER 7 eer	11 eer	14 eer	ES Refrigerator	ES Dishwasher	ES Clothes washer	Devices count=5	count=10	count=15	Electric Vehicle
Programmable Thermostat			* -14%					* 0%				* 0%				* -1%
Multipane Windows		* -16%														
Insulation R value	R <19															
	19 <R < 29															
	R>30															
Air Conditioning EER	7 eer	* -15%									* -31%					
	11 eer	* 12%									* -4%					
	14 eer	* 38%									* 24%					
ES Refrigerator																
ES Dishwasher								* 5%								
ES Clothes washer		*-11%														
Devices	count=5															
	count=10															
	count=15															
Electric Vehicle		* -49%														

LEGEND

Increase in electricity consumption

No effect

Net energy savings

* Statistically significant results to 10% level

Figure 8: Predicted increases or decreases in electricity consumption for eight different sources of marginal technical change in 120 homes in Austin, TX.

The rows delineate subset of homes with the indicated technologies installed, e.g., the row labeled "Programmable Thermostat" indicates the subset of all homes with a programmable thermostat. The technologies across the columns define marginal technical change within the subset of homes defined by the row. Thus, the cell values and color coding indicate differences in predicted electricity consumption for homes with the column technology installed given the row technology is installed.

Figure 8 shows several important potential trends. First, the observed effect of technical change is most significantly influenced by the presence of a programmable thermostat. With respect to marginal technical change within space conditioning, we generally observe that “enough” efficiency improvements overcome any behavioral responses, eventually producing net energy savings with the exception of marginal technical change between AC efficiency (measured by the EER value) and programmable thermostat. Second, the fitted values indicate homes that are relatively more efficient with respect to air conditioning generally do not appear to leverage these efficiency gains for appliance services, as indicated by the primarily white colored cells above the diagonal in the appliance columns. However, the degree to which homeowners may leverage efficiency gains from appliances for space conditioning is mixed and less clear. A similarly mixed message is observed when considering whether homeowners might leverage efficiency gains for energy service expansions, as indicated in the cell values and colors in the columns for devices and Electric Vehicles.

2.5. Discussion

Previous quantitative assessments of efficiency change assume discrete efficiency changes and generally do not control for variation in the relative technical state of the home, which can occur both within and across end-uses. Our results, which are limited to short-run responses, challenge this approach.

We show empirically that the effect of efficiency interventions for space conditioning is relative to the baseline technical performance of homes. This could be due to purely technical factors (such as increased window panes subsequently changing the performance of attic insulation), behavioral responses, or some combination thereof.

Other researchers have implied a declining rebound effect with increasing efficiency, where consumers approaching satiation for a given energy service take back fewer efficiency gains [Lovins 1998; Binswanger 2001; Madlener and Alcott 2009]. If this were the case, we would expect that "enough" technical improvement within air conditioning would eventually overcome behavioral responses, leading to net energy reductions. With varying degrees of statistical significance, this is observed for marginal technical change within space conditioning (including a programmable thermostat, AE EER value, insulation R-value, and window panes) except interactions between a programmable thermostat and air conditioning efficiency ratio. It could be that householders in our sample adjust their thermostat settings independent of the efficiency of their air conditioning. It could be that the newer, more efficient air conditioners are oversized.

Our results further suggest that empirical studies aiming to estimate the magnitude of the direct rebound effect using aggregate fuel or electricity consumption may be misleading unless they control for important sources of technical variation in their sample. In particular, our sample demonstrates marginal technical change is particularly sensitive to the presence of a programmable thermostat. We also find that homeowners may leverage efficiency gains in one end-use for another, which would confound studies that do not represent the technical state of a variety of end uses. As a result, the practice of borrowing short-term price elasticities from discrete studies to speak more broadly about the magnitude of rebound seems misleading, particularly given that households are subject to ongoing, long-term exogenous (e.g., Federal standards) and endogenous (e.g., voluntary standards) technical change.

Previous research has emphasized the importance but unknown rebound implications of the income effect across energy intensive services [Binswanger 2001;

Madlener and Alcott 2009; Saunders 2013]. Here, our sample does not appear to be rebounding into appliance services but may be rebounding into devices, particularly leveraging gains from the adoption of a programmable thermostat for addition device use. This phenomenon might be an inclination toward adoption and use of devices in some households. However, opposite trends are noticed for houses with electric vehicles. This could be explained by underlying environmental valuations of EV adopters or income effects associated with purchase or operation of an EV. These results support the consideration of energy service expansions in demand-side approaches.

While results are mixed, they do indicate that demand-side programs might consider a portfolio of efficiency interventions opposed to interventions aimed at discrete efficiency changes. Such an approach would reduce the possibility that consumers "take back" efficiency gains within and across energy services. More empirical research with a large, more representative sample could be needed to better understand the net economic and environmental effect of efficiency gains. This work provides some insights on how to prioritize such efforts.

We emphasize that our sample does introduce geographic (urban, cooling dominated climate) and income (mean annual income of $138k) biases, thus limiting the generalization of the quantitative results. It is uncertain if households in other geographies and income brackets would demonstrate similar qualitative results, and we encourage readers to interpret results accordingly.

3. An Empirical Assessment of Residential Rooftop Photovoltaic Panel Technology Choice and Performance

In an attempt to address growing concerns about climate change and fossil fuel dependence, the US government has fostered the implementation of renewable energy sources such as wind, biomass, geothermal, hydroelectricity and solar energy. The technical potential for energy reductions from renewable sources has been the subject of extended research [NYCERDA, 2014; NREL, 2013; Lund, 2007].

In 2008, only 7% of the US energy was supplied by renewable sources, of which 1% came from solar energy [EIA, 2009]. By 2014, the US solar generation capacity has grown by 418% to cover 1.13% of the total US electricity generation capacity [EIA, 2015]. Across the distributed generation landscape, residential PV has seen the most consistent growth of any segment for years, with a 45% increase over the third quarter of 2014 [SEIA, 2014].

There are mainly two types of solar technologies that dominate the US market: photovoltaics (PV) and concentrating solar power (CSP). CSP systems use mirrors to focus sunlight onto a receiver and heat a fluid to a high temperature. The thermal energy is then converted into electricity. The CSP generating stations are usually centralized and produce power on the utility side of the meter rather than the consumer side.

The most widespread technology for residential solar energy generation is photovoltaic panels (PV). These panels are usually mounted on the house rooftop and convert sunlight into direct current electricity that is converted to alternating current electricity using an inverter system. By supplying electricity onsite, the solar systems reduce the transmission costs of electricity generated from remotely located power plants. Most of the PV systems in the solar market are grid-connected, with generating capacities ranging from hundreds of watts to tens of megawatts [Bradford, 2006]. The grid-connected PV systems are directly plugged into the local utility and do not require a battery, as the grid consumes the excess electricity generated by the system when production exceeds the household's needs. In this case, the excess of electricity produced is injected into the grid and the home-based photovoltaic system becomes a mini-power generation station.

Researchers and policymakers globally underscore the need for renewable energy to displace fossil fuel consumption in an effort to mitigate climate change. Previous studies estimated that part of fossil fuel production can be displaced by solar and wind resources [Lopez et al., 2012], with ranges in estimates being driven primarily by uncertainty in the technical performance of these resources. The US total primary energy consumption achieved almost 28,500 TWh in 2013, with 66% produced from fossil fuels [EIA, 2014]. Lopez et al. (2012) estimate that the annual technical potential from renewable energy could reach 481,800 TWh, with over 86% of the generation potential accounted for by solar and wind power production. Solar photovoltaic technologies are expected to lead all other technologies in technical potential (283,600 TWh), but only 0.28% of the solar PV generation capacity comes from residential rooftop PV [Lopez et al., 2012]. However, the uncertainty in fossil fuels that are displaced are generally limited to purely technical and environmental factors (e.g., intermittency). For centralized renewable supplies – such as wind – assuming that renewables exclusively displace conventional sources of grid electricity may be fair. However, distributed resources, i.e., solar photovoltaic (PV) panels demonstrate an entirely different ownership and operational profile that further complicates their ultimate performance. Previous researchers indicate that most PV systems do not achieve the expected electricity production. For example, Silverman (2008) argues that, on average, solar PV panels generate only one-fifth of their peak capacity daily (i.e. average capacity). The current average conversion efficiency of solar PV systems in the market is around 17%, which demonstrates that there is a great potential for PV technologies to increase its capabilities in converting sunlight to electrical voltage [Maslin, 2009; Rothfield, 2010].

Of the available renewable sources, rooftop PV technologies are considered as the most attractive renewable option to consumers due to its flexibility in land and space choices and its long service life that averages 25 years [Borenstein, 2008]. Nevertheless, it is currently widely acknowledged that the capital and operating costs of solar PV installation are larger than its financial benefits, including the avoided costs from electrical transmission losses [Borenstein, 2008; Heal, 2009]. Despite this financial disadvantage of PV installation, the state of California reported over 134,000 installations of grid-connected systems in the residential sector, as of February 2015 [CSI, 2015]. Therefore, consumers' decision to adopt solar technologies might be influenced by other factors, beyond the "rational choice" model that drives individuals to choose options maximizing their expected utility [Kahneman, 2011; Jackson, 2005].

In determining the principal drivers of PV installation, the solar energy literature has focused on the cost-benefit analysis of PV installation to consumers and the socioeconomic factors that motivate PV installation. Factors that could drive PV installation rates might be the consumer's environmental consciousness, number of the household residents, their age, educational level, and prestige [Durham, 1988]. Simon (1991) argues that the decision-making rationality of consumers is influenced by their cognitive limitations, information availability, and time constraints to make their decisions [Simon, 1991]. Jacobsson and Johnson (2000) emphasize the effect of social networking on raising consumer consciousness to the viability of the installation of renewable technologies [Jacobsson and Johnson, 2000; Roger, 2005]. This mechanism is referred to by the literature as "the spillover effect". In addition, empirical evidence of peer effects shows that the number of PV adoptions in a zip code area impacts householder choice to adopt solar panels [Bollinger and Gillingham, 2010]. However, beyond the purely financial and social factors, behavioral economists argue that consumer decisions to adopt solar PV might be driven by unobserved factors [Manski, 1993; Moffitt, 2001; Soetevent 2006; Hartmann et al. 2008]. In the solar industry, the concept of the "environmentally friendly" individual is certainly a salient definition of consumers who prioritize the environmental impact of their technological choices to maintain their identity as "socially responsible" consumers [Brekke, Kverndokk, and Nyborg 2003; Young et al. 2009; Nyborg, Howarth, and Brekke 2006].

Despite a seventy-fold increase in global solar photovoltaic installations between 2000 and 2012 [Barbose et al. 2013], behavioral analysis of household response to PV adoption lags. Previous studies have investigated how consumers modify their energy use patterns after the adoption of energy efficient technologies. The concept of "rebound effects" is perhaps the most salient in the neoclassical economics realm. This microeconomic phenomenon occurs when an increased efficiency decreases the implicit cost of energy services, which drives the consumer to increase the quantity demanded [Greening et al., 2000; Moniz et al. 2012; Borenstein 2014]. However, the rebound effect is mainly driven by supply and demand conditions and does not entirely capture the non-monetary and psychological factors that influence consumer energy use patterns [Tiefenbeck et al., 2013]. Moral licensing is another behavioral phenomenon that arises when "people can call to mind previous instances of their own socially desirable or morally laudable behaviors" making them "feel more comfortable taking actions that could be seen as socially undesirable or morally questionable" [Miller and Effron, 2010]. In this context, pro-environmental behaviors that drive consumers to choose green technologies might emanate from their desire to reduce the repercussions of another environmentally harmful behavior such as an increase in their consumption of conventional electricity [Jacobsen et al., 2010].

As far as the solar energy literature, the few existing studies on consumer responses to PV installation are based upon self-reported behaviors that demonstrate mixed results and provide no insight into the observed performance of distributed solar. Some studies report that consumers with solar energy technologies correlate the timing of end uses with solar availability [Schweizer-Reis et al 2000; Dobynn and Thomas 2005]. Kierstead (2007) found that most PV owners reported no changes in behavior, some reported minor changes, and few respondents reported significant behavior changes. Comparing descriptive statistics, Hass et al. (1999) suggest that low-energy Austrian households (>4500 kWh per household per year) increased grid electricity consumption by 10-50% following PV installations, whereas high-energy households reduced grid energy consumption by 1%-35%. About 80% of householders in Austin TX self-reported no change in energy demands [McAndrews, 2011].

The literature attempts to qualitatively assess the performance of solar PV technologies on residential energy demand and grasp some of the non-financial and economic factors that could impact consumer choice to install PV panels. However, these studies are vey limited in that i) they are based on self-reported household information, ii) they do not quantitatively assess consumption patterns upon PV installation iii) they examine only short-term behavioral responses to PV technology installation, and iv) they do not control for unobserved factors that drive consumer choice to adopt solar PV.

This study, thus, provides a unique opportunity to empirically assess the impact of solar PV adoption on electricity demand and emphasizes the importance of modeling the unobserved factors that drive consumer decisions to install solar. Our assessment is based on metered electricity consumption and production data. However, we assume that the consumers that own solar panels whether they produce all energy used on site (i.e. Household energy use=On-site production from PV) or fulfill part of their energy needs from the grid (i.e. Household energy use= On-site production from PV+ Grid energy).

3.1. Material and Methods

The data used in this study were obtained from the Pecan Street Research Institute (PS). PS is a 501(3)c non-profit that has partnered with The University of Texas at Austin and industry leaders to advance the understanding of resource consumption in homes. Pecan Street's core services include collecting, managing, and disseminating high-resolution research data characterizing residential resource consumption and respective determinants.

Static data were collected using home energy audits and household surveys. Audit data include approximately 300 fields representing home physical characteristics. Several PS participants have taken extensive annual surveys characterizing energy and water technology choices, uses, and demographics.

The PS project collects electricity consumption and PV production at 1-second intervals. This study aggregates the data in one-month (or one-year) intervals and uses consumption and production data for 16 months (from September 2013 to December 2014). Our study sample contains 370 homes that reported high-resolution, continuous electricity use and production data, as well as information on household physical characteristics.

For the houses in our study sample, the kWh electricity "use" or "consumption", "production", and "Grid" are defined as follows:

$$Y_i = Y_{prod,i} + Y_{grid,i} \qquad \textbf{Equation 4}$$

where: Y_i = Electricity use (also referred to as "consumption") for household i

$Y_{prod,i}$ = Electricity production from PV panels (also referred to as "generation")

For household i: $\begin{cases} = 0 \text{ if household i does not have solar PV panels} \\ \geq 0 \text{ if household i has solar PV} \end{cases}$

$Y_{grid,i}$ = Electricity provided by the Grid for household i

However, not all of those 370 homes in our sample are used in the econometric models because of missing data. Table 7 summarizes our study sample.

Table 7: Summary statistics of the explanatory variables used in the analysis; *dummy variables* determine whether or not the house has a specific item (e.g. solar panel=1 if the house has a solar panel installed, =0 if not).

Category	**Variable**	**Mean and Standard Deviation (2013 – 2014)**
Climate	Cooling degree days (per month)[+]	Mean= 261; s = 245
Structural factors	Floor area (square feet)	Mean= 1986; s = 703
	Age of the house	Mean= 25.7; s = 25.3
Demographic factors	Household members (Occupancy)	Mean= 2.64; s = 1.15
	Tenure	Mean= 6.32; s = 7.29
	Household income	Mean= \$138k; s = \$101k
	Post-graduate degree	Count = 85
Self-reported behaviors	TV hours watched per month	Mean= 145; s = 106
	Dishwasher loads per month	Mean= 12; s = 8.28
	Clothes washer loads per month	Mean= 16.6; s = 8.79
	Hours per month worked from home	Mean= 103; s = 54.9

Table 7 continued:

Technology choices	Insulation R value	Mean= 29.8 ;s = 10.9
	AC Energy Efficiency Ratio	Mean= 11; s = 1.61
	Number of devices++	Mean = 8.17; s =4.75
	Multi-pane windows	Count = 86
	Energy star refrigerator	Count = 25
	Energy star dishwasher	Count = 34
	Energy star clothes washer	Count =34
	Solar panels	Count = 80
	Electric vehicle	Count =34
	Programmable thermostat	Count=108
Energy	Monthly Electricity Consumption (KWh/month)	Mean= 887; s = 613
	Annual Electricity Consumption (kWh/year)	Mean= 11,272; s = 7237
	Annual Electricity Production for solar panels (kWh/year)	Mean= 7,085; s = 1,040

+ For any given month, cooling degree days are assumed constant across households as they are all located in Austin, TX [National Weather Service, 2013].
++ Devices include computers, TVs, tablets, cable or satellite boxes, DVRs/DVD/VCR/BluRay, Stereo systems, and gaming systems.

To evaluate the response of homeowners to photovoltaic technology, we i) build electricity demand models to assess the impact of solar panels adoption on monthly and annual electricity use, ii) investigate the impact of modeling technology choices on solar panels performance, iii) model household electricity consumption using predicted solar panels adoption probabilities, and iv) evaluate the combined effect of solar panels and other demand-side technologies on electricity use.

Figures 9a and 9b show the distributions of electricity consumption and on-site PV production for houses in our study sample.

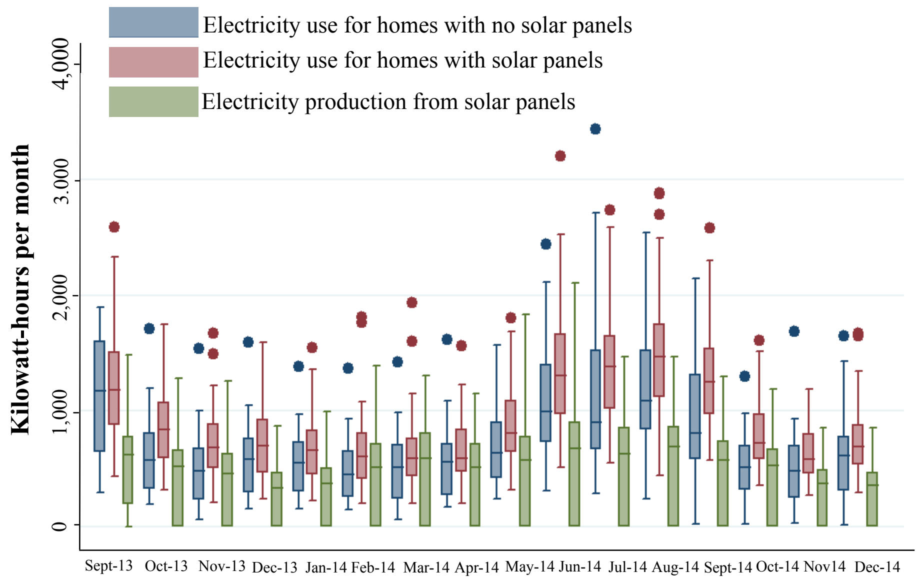


Figure 9a: Distribution of monthly electricity consumption and production from solar panels for houses in the study sample, from September 2013 to December 2014.

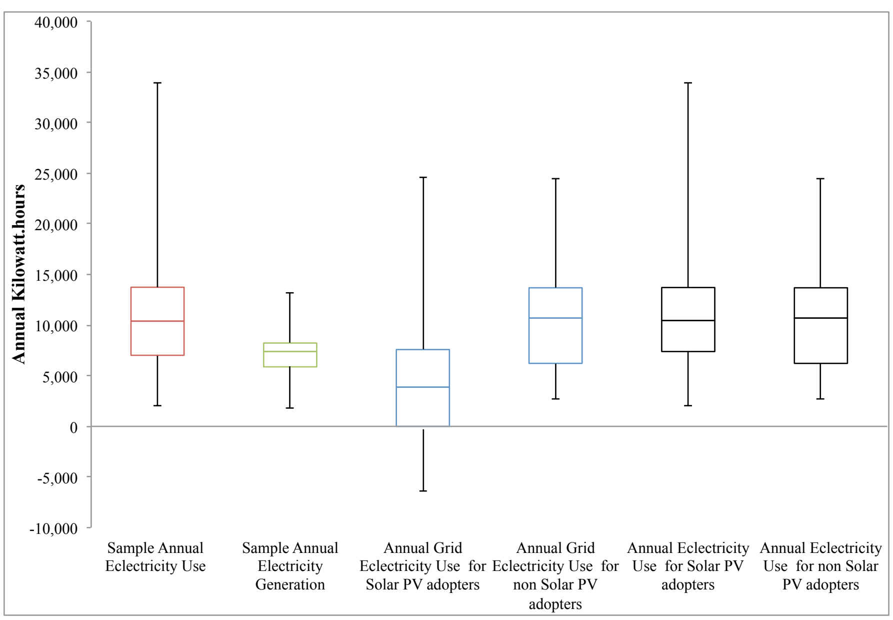


Figure 9b: Distribution of annual electricity use, “grid”, and generation for houses in the study sample. Note that the annual “grid” electricity use is assumed to be equal to the annual electricity consumption minus the electricity production from solar panels.

Figure 9a shows that household electricity consumption and production from PV panels reflect the seasonality expected of a climate dominated by cooling loads such as Texas. However, the solar generation capacity of houses with PV panels does not increase significantly in the summer months, when Texas achieves peak solar radiation potential, as would be expected. Overall, the data distribution indicates that houses with installed rooftop PV consume more electricity, on average, than houses with no solar technology.

Figure 9b present a more aggregated summary of annual consumption and production patterns for the households in our study sample. The distribution of annual electricity use shows that electricity demand is not significantly different for houses with PV panels, compared to those without PV panels. However, assuming that PV adopters do not generate an excess of on-site electricity, Figure 9b indicates that households that own PV panels consume, on average, less "grid" electricity than homeowners without solar panels.

The above preliminary statistics compare the overall PV-adopters energy consumption and production patterns to the non-PV adopting households. However, it does not accurately capture the performance of PV panels due to the varied household and householder factors that influence net consumption. The variability in household electricity use might be explained by other physical and behavioral characteristics, beyond solar PV installation. A combination of regression models and discrete choice modeling techniques are used to investigate the differences in electricity use for houses that choose to adopt solar panels compared to those who do not. The modeling framework steps are disaggregated as follows:

i) Monthly electricity demand model: I use mixed regression model, with fixed and random household effects to investigate the impact of seasonality on the performance of PV panels, using the cooling degree days as a proxy to capture the weather externalities and a dummy variable for PV installation.

ii) Annual electricity demand model I: I build a multiple regression model of households annual electricity use to assess the differences in annual electricity consumption for PV and non-PV adopters, using a dummy variable for PV installation.

iii) Annual electricity demand model II: I develop a multiple regression model of households annual electricity use to assess the impact of household choice to adopt PV on their annual electricity use. In this model, I use the estimated probabilities of PV adoption from the discrete choice modeling results.

iv) Annual electricity demand model III: I develop a multiple regression model of household annual electricity use to assess the impact of household choice to adopt PV on their annual electricity use, by controlling for the unobserved factors of PV installation, using DCM results of electric vehicle and PV adoption.

v) Annual electricity demand with interactions I: We develop a mixed regression model of household monthly electricity use and append interactions terms to test whether consumers use energy gains from solar PV toward other uses. In this model, I use a dummy variable to indicate the presence of PV panels.

vi) Annual electricity demand with interactions II: I use multiple regression and discrete choice models to investigate how consumers leverage solar energy production for energy services by controlling unobserved factors of solar PV adoption.

3.2. TREATING PV INSTALLATION AS A DUMMY VARIABLE

I first use a mixed effects regression model of electricity consumption to account for repeated measures with both fixed (e.g., floor space) and random effects. The household effect on the outcome is assumed to be random. Therefore, I model it using random intercepts (similar applications in Attari et al. (2010) and Revelt and Train (1998)). The general model is specified in Equation 5:

$$Y_{it}^{\lambda_1} = \beta_0 + \beta_1 CDD_t + \sum_{j=1}^{k} \beta_j S_{ij}^{\lambda_j} + \sum_{j=k+1}^{m} \beta_j D_{ij}^{\lambda_j} + \sum_{j=m+1}^{n} \beta_j B_{ij}^{\lambda_j} + \sum_{j=n+1}^{p} \beta_j T_{ij} + \beta_{p+1} PV_i + \sum_{j=p+2}^{l} \beta_j \left(T_{ij} \,.\, PV_i\right) + \beta_i R_i + \varepsilon_{it}$$

Equation 5

where Y_{it}^{λ} represents the electricity consumption observations in KWh, raised to the power λ

β_j (j from 0 to 1) are the coefficient estimates for fixed effects (the betas are the same for all the houses)

β_i are the coefficient estimates for random effects where each household has its own coefficient

CDD_t represents Cooling Degree Days in Austin obtained for 16 months (from September 2013 to December 2014)

S_{ij}^{α} represents a series of household structural factors, raised to the power α

D_{ij}^{θ} represents a series of household demographic factors, raised to the power θ

B_{ij}^{δ} represents a series of household self-reported behavioral factors, raised to the power δ

T_{ij} represents a series of technology choices

PV_i is a dummy coding to identify houses with photovoltaic panels installed

R_i represents the household identification codes

ε_{it} represents the error terms

I first investigate the influence of seasonality-represented by CDD in evaluating the performance of solar PV panels and their impact on monthly electricity consumption. Equation 6 shows the model specification for monthly electricity use, developed by (1) applying stepwise regression to screen predictors for inclusion in the final model and test for assumptions of linearity (2) dropping statistically insignificant predictors and (3) identifying transformations appropriate for model fit and normality using the BoxCox method (Box, 1964). Predictors in Equation 6 include the installation of solar PV panels, the number of devices (computers, televisions, tablets, and phone), and the installation of three types of efficiency technologies: shell insulation, programmable thermostat, and Energy Star clothes washer. Model results are presented in the Supplemental Information (SI-Table 1).

$$log(Y_{it}) =$$

$$\beta_0 + \beta_1 CDD_t + \beta_2 . \frac{1}{\sqrt{HouseArea_i}} + \beta_3 . Devices_i + \beta_4 . RValue_i$$

$$+ \beta_5 . ESClothes\ washer_i + \beta_6 . ProgThermostat_i + \beta_7 PV_i + \beta_8 R_i + \varepsilon_{it}$$

Equation 6

Results indicate that the variation in Cooling Degree Days does not affect the solar PV performance (SI-Table 1). Therefore, I use the annual energy demand model to assess the impact of solar panels installation on annual electricity use, as described by Equation 7. In this model, the PV production variable is presented as a dummy variable, where PV adopters are coded as "1" and non-PV adopters are coded as "0".

$$log(Y_i) =$$

$$\beta_0 + \beta_1 HouseArea_i + \beta_3 Occupancy_i + \beta_4 Income_i + \beta_5 PV\ (dummy)_i + \varepsilon_i$$

Equation 7

Where Y_i represents annual electricity use (kWh), β_i are regression coefficients, and ε_i are error terms.

Table 8 shows regression results of estimated differences in annual electricity use for houses with and without PV panels.

Table 8: Regression results of annual electricity consumption with solar panels as a dummy variable (see Equation 7)

Explanatory variable	**Coefficient estimate**	**p-value**	**% change in consumption for 1 unit increase in X variable**
House Area (square feet)	0.000284 (0.0000453)	0	0.0284%**
Electric Vehicle	0.173 (0.0647)	0.008	18.9%**
Income	0.000000651 (0.000000279)	0.021	0.0001%**
Occupancy	0.0588 (0.0251)	0.021	6.06%**
Photovoltaic panels (dummy)	**-0.00194 (0.079)**	**0.98**	**-0.194%**
Constant	8.32 (0.108)	0	-

** p-value<0.01 , * p-value<0.1, + p-value<0.2

The regression estimates from the annual electricity demand model (i.e. Equation 7) indicate that four out of five predictors are statistically significant: house area, electric vehicle ownership, income, and occupancy. Results demonstrate that houses owning an electric vehicle are predicted to consume 19% more electricity than the rest of the study population. The regression estimates from the annual electricity demand model indicate that the PV adoption dummy variable is not statistically significant in explaining the variation in annual electricity demand.

3.3. Discrete Choice Modeling

The econometric specification and estimation of the demand for electricity have long been a subject of interest as it posed a rich set of problems to econometricians. Multiple studies have attempted to model jointly the demand for appliances and the demand for electricity. Within this context, it becomes important to test the validity and statistical significance of dummy variables typically used in electricity demand equations, such as described in Equation 5 [Dubin and McFadden, 1984]. As homeowners do not necessarily act in a reasonably consistent microeconomic manner, I use a discrete choice model – a logistic model- to better grasp the unobserved preferences that drive consumers to choose the adoption of PV panels. The discrete choice framework has been applied in multiple studies on the determinants of residential energy behavior, such as appliance choice [Dubin and McFadden, 1984; Vaage, 2000; Liao and Chang, 2002; Mansur et al., 2008; and Goto et al., 2011]

I started by screening for statistically significant variables describing household characteristics to specify the logistic (or "logit) PV model (Equation 8). The "logit" model in Equation 8 estimates the probability of adopting photovoltaic panels:

Equation 8

$$\Pr(Y_i = 1|X_1, X_2, \dots, X_8) = \frac{e^{\beta_0+\beta_1.X_1+\beta_2.X_2+\cdots+\beta_8.X_8+\varepsilon_i}}{1 + e^{\beta_0+\beta_1.X_1+\beta_2.X_2+\cdots+\beta_8.X_{8+}+\varepsilon_i}}$$

where:

Y= PV adoption for household i

X_1= Household tenure. It is the number of years they spent in the house

X_2= Household income (in $)

X_3= The Age of the house (in years)

X_4= Dummy variable that is equal to 1 if the householder has a Postgraduate degree

X_5= Number of dishwasher loads per month

X_6= Number of clothes washer loads per month

X_7= Insulation R value

X_8= Dummy variable that is equal to 1 if the household has an electric vehicle

β_o to β_8 are regression coefficients and ε_i error terms.

Table 9 shows the Discrete Choice Modeling (DCM) results of the household characteristics that influence the probability of solar panel adoption.

Table 9: Logistic regression model results for PV probability estimate (see Equation 8)
Adjusted R^2=0.3166

Explanatory variable (X_i)	**Coefficient estimate**	**p-value**
Age of the house	-0.0629 (0.0112)	0 **
Postgraduate education	1.034 (0.415)	0.013 *
Householders' tenure	-0.0589 (0.0267)	0.027 *
Income	0.00000364 (<0.000001)	0.039 *
Electric Vehicle	1.255 (0.61)	0.04 *
Number of clothes washer loads	-0.0506 (0.026)	0.052 *
Number of dishwasher loads	0.0446 (0.0305)	0.143 $^+$
Insulation R value	0.0341 (0.0239)	0.152 $_+$
Constant	118 (55.6)	0.028 *

** p-value<0.01 , * p-value<0.1, $^+$ p-value<0.2

Table 9 shows the DCM coefficient estimates and their level of statistical significance. Results show that six of the eight predicting variables are statistically significant to the 10% level: the age of the house, the householders' educational level, their tenure, their income, the clothes washer loads, and whether they own an electric vehicle. DCM results indicate that older houses are less likely to choose solar panels than newly built ones. In addition, highly educated consumers have a higher probability to adopt solar technologies, as well as householders with electric vehicles. Results further indicate that newly moved tenants are more likely to install solar PV than older residents. This finding is expected as new residents are offered PV incentives during the real estate acquisition process.

Figure 10 compares the predicted probabilities derived from the model specified in Equation 8 and Table 9 to the observed dummy variable describing the ownership of solar panels.

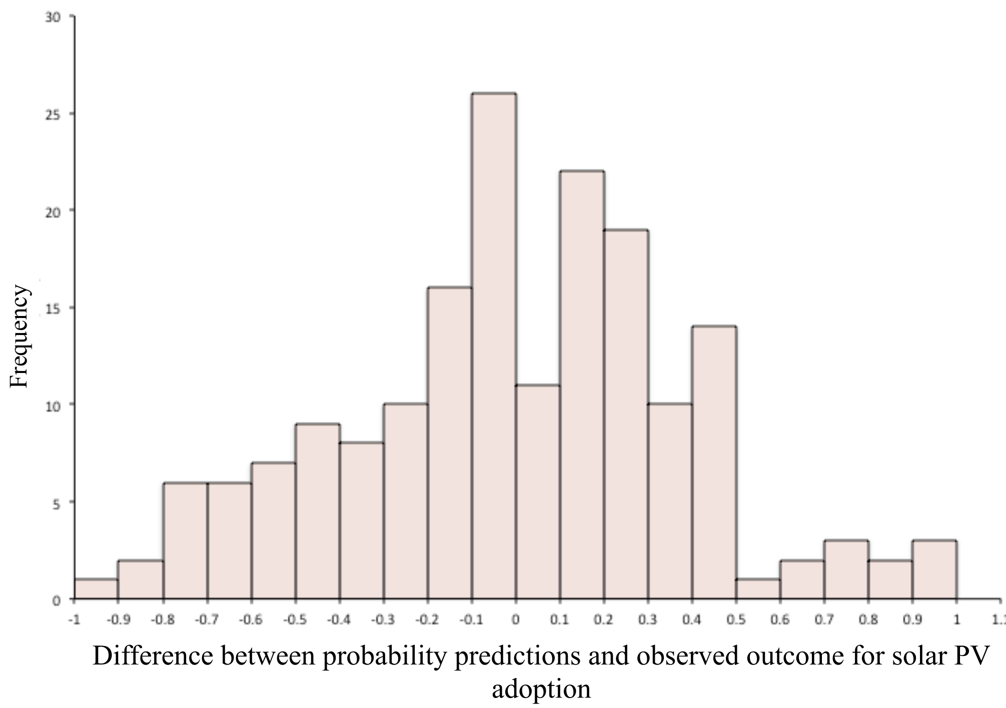


Figure 10: Distribution of the difference between predicted and observed probabilities of solar panel adoption

Figure 10 indicates that the model errors are distributed around zero, which suggests that the probability estimates of solar panels adoption generated from the DCM in Equation 8 consistently describe the factors that might influence the householder decision to choose to adopt renewable technologies. Thus, I used these predicted probabilities to assess the impact of PV technologies on household electricity demand. Equation 9 describes the regression model used to investigate the implications of choosing renewables on electricity use.

$$log(Y_i) = \beta_0 + \beta_1 HouseArea_i + \beta_2 Tenure_i + \beta_3 Occupancy_i + \beta_4 Income_i + \beta_5 PVprobability_i + \varepsilon_i$$

Equation 9

where Y_i describes annual electricity use (KWh), ε_i are error terms, and $PVProbability_i$ are the estimated PV probabilities from the discrete choice model in Equation 8.

Table 10 shows the regression results of the annual electricity demand model using DCM estimates of the probability of solar PV adoption.

Table 10: Regression model for annual electricity consumption using PV discrete choice model (see Equation 9) Adjusted R^2=0.3981

Explanatory variable	**Coefficient estimate**	**p-value**	**% change in consumption for 1 unit increase in X variable**
House Area (square feet)	0.000258 (0.0000526)	0**	0.0258%
Income	0.000000512 (0.000000274)	0.064*	0.0000512%
PV adoption probability	0.2027468 (0.1099063)	0.068*	22.5%
Electric Vehicle (dummy)	0.1180854 (0.0731098)	0.109^{+}	12.5%
Occupancy	0.0347874 (0.0262113)	0.187^{+}	3.54%
Constant	8.374261 (0.1007832)	0**	-

** p-value<0.01 , * p-value<0.1, $^{+}$ p-value<0.2

Regression results reveal three variables to be statistically significant: House area, income, and PV adoption probability generated from the DCM. Contrary to results of the regression models treating PV adoption as a dummy variable (Table 8), results in Table 10 show PV adoption to be statistically significant in predicting annual electricity consumption. In fact, household electricity demand is estimated to be 23% higher for houses that choose to install solar panels.

The discrete choice framework applied to solar PV adoption (see Table 9) shows that houses with an electric vehicle are more likely to choose to install solar panels, probably for some “environmental consciousness” or “technological propensity” that cannot be easily quantified. Therefore, to further separate the influence of different unobserved factors on the probability to adopt “clean” technologies, we iterate the DCM for electric vehicle and solar PV adoption to build the final electricity demand model, using logistic and multiple regression techniques, as described by the following methodological and theoretical framework (see Figure 11 and Equations 10, 11, and 12):

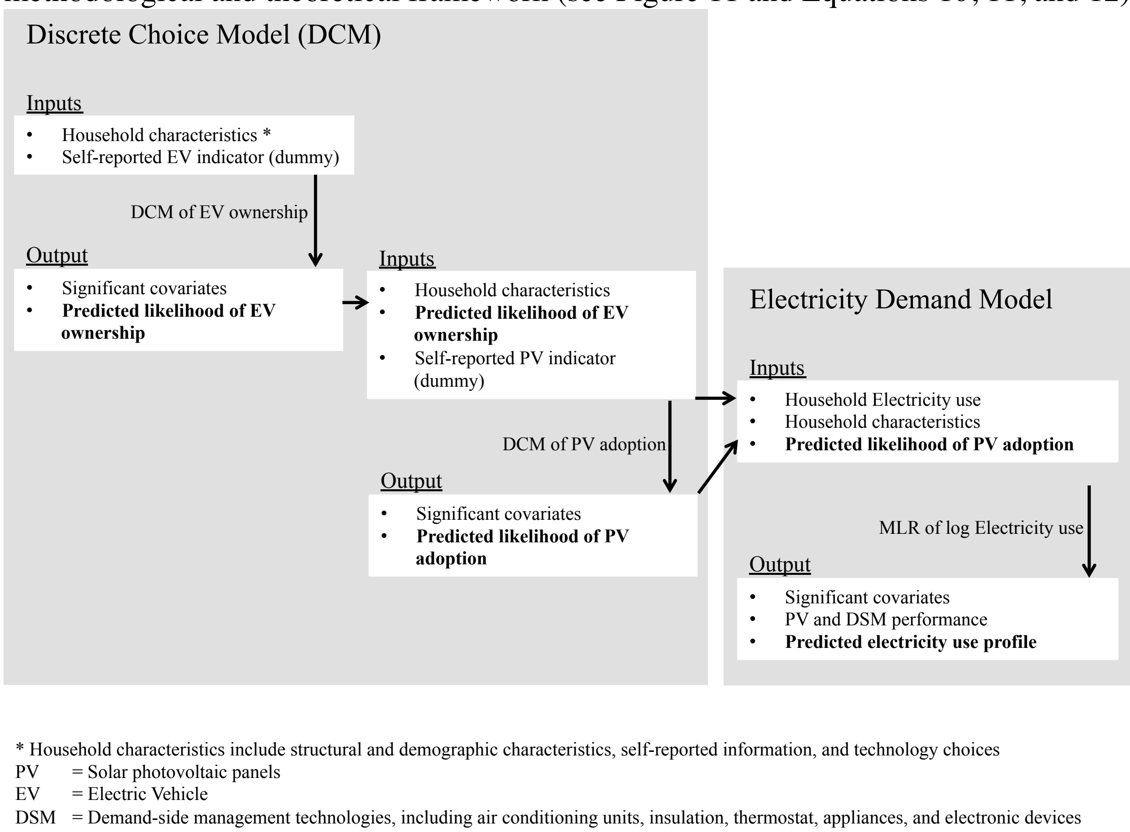


Figure 11: Methodological framework describing the combination of discrete choice experiments with electricity demand modeling

$$\log(Y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + \beta_{k+1}\widehat{\mathrm{PV}_{logit,i}} + \varepsilon_i$$ **Equation 10**

$$\mathrm{PV}_{\mathrm{logit,i}} = \Pr\left(\mathrm{PV}_{\mathrm{i}} = 1 \middle| Z_1, Z_2, \dots, Z_m, EV_{logit}, i\right) = \frac{e^{\beta_0+\sum_{j=1}^{m}\beta_j Z_j+\beta_{m+1}\widehat{EV_{logit,i}}+\varepsilon_i}}{1+e^{\beta_0+\sum_{j=1}^{m}\beta_j Z_j+\beta_{m+1}EV_{logit,i}+\varepsilon_i}}$$

Equation 11

$$\mathrm{EV}_{\mathrm{logit,i}} = \Pr(\mathrm{EV_i} = 1|W_1, W_2, \ldots, W_n) = \frac{e^{\beta_0+\sum_{j=1}^{n} \beta_j W_j + \varepsilon_i}}{1 + e^{\beta_0 + e^{\beta_0+\sum_{j=1}^{n} \beta_j W_j + \varepsilon_i}}}$$

Equation 12

where Y_i represents annual electricity use (KWh)

X_i are the selected predictors of electricity demand

$\widehat{PV_{logit,i}}$ is the estimated probability for household i to adopt solar PV

Z_i represent the factors that impact solar PV adoption

$\widehat{EV_{logit,i}}$ is the estimated probability for household i to purchase an electric vehicle

W_i represent the factors that impact electric vehicle ownership

β_i are modeling coefficients and ε_i are error terms

The discrete choice estimates of the probability of purchasing an electric vehicle (Equation 12) were used as a predicting factor for solar PV adoption (Equation 11). Then, the estimated probabilities of PV installation were injected into the electricity demand model (Equation 10).

The DCM results from the Electric vehicle and PV logistic models are presented in Tables 11 and 12 respectively.

Table 11: Logit regression model results for EV probability estimate (see Equation 12)

Explanatory variable	**Coefficient estimate**	**p-value**
PV (dummy variable)	1.06 (0.445)	0.017*
Number of vehicles	0.692 (0.295)	0.019*
Occupancy	-0.396 (0.211)	0.061*
House Area (sq ft)	-0.000244 (0.000335	0.466
Workday	0.249 (0.459)	0.588
Constant	-2.27 (0.848)	0.007**

Table 12: Logit regression model results for PV probability estimate (see Equation 11), Adjusted R^2= 0.6149

Explanatory variable	**Coefficient estimate**	**p-value**
EV_{logit}	28.2 (4.99)	0**
Age of the house	-0.0746 (0.0165)	0**
Number of dishwasher loads	0.0949 (0.0385)	0.014*
Insulation R-value	0.0836 (0.0334)	0.011*
Income	0.00000454 (0.00000253)	0.073*
Postgraduate education	0.881 (0.598)	0.141^+
Constant	-7.86 (1.82)	0**

** p-value<0.01 , * p-value<0.1, $^+$ p-value<0.2

Table 11 indicates that solar PV adoption, occupancy, and number of vehicles are significant drivers of electric vehicle ownership. Houses with a larger number of conventional fossil fueled vehicles are more likely to purchase an electric vehicle.

I plot differences between observed and predicted electric vehicle and PV adoption estimates from the discrete choice framework to assess the accuracy and goodness of fit of the selected models, as presented in Figures 12a and 12b.

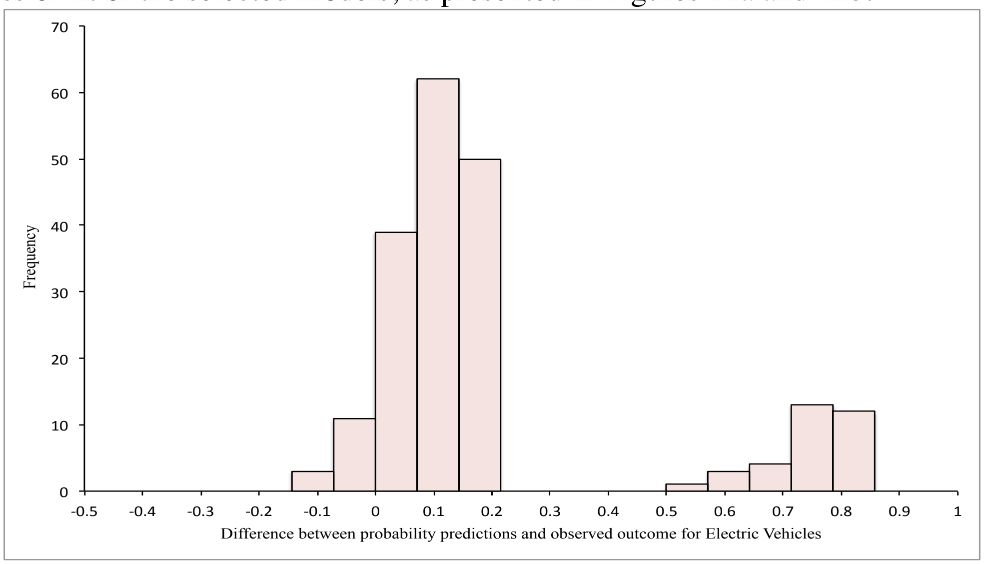


Figure 12a: Distribution of the difference between predicted and observed electric vehicle adoption

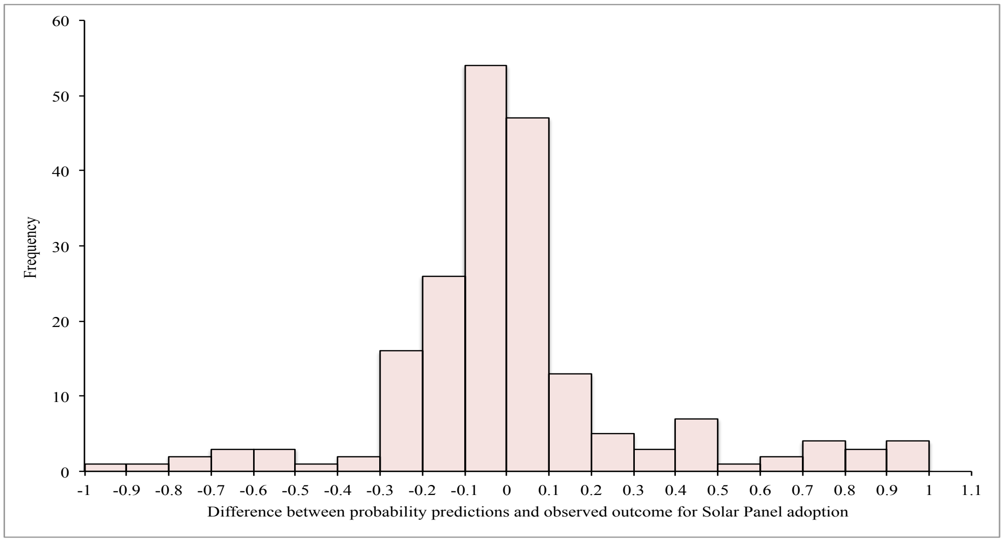


Figure 12b: Distribution of the difference between predicted and observed solar panels adoption

The discrete choice framework diagnostics indicate that the modeling errors are centered around zero. Therefore, the selected discrete choice models successfully capture the unobserved drivers of both Electric Vehicle and solar PV adoption preferences. I then screen for the household predictors that better explain variation in electricity consumption and use the estimated probabilities of solar PV adoption to develop the final annual electricity demand model (Equation 10). Table 13 presents regression results of electricity use as a function of house area, income, occupancy, electric vehicle ownership (dummy), and estimated PV adoption probability.

Table 13: Regression model for annual electricity consumption using PV discrete choice model, second model (see Equation 10)

Adjusted R^2=0.3902

Explanatory variable	**Coefficient estimate**	**p-value**	**% change in consumption for 1 unit increase in X variable**
House Area (square feet)	0.000292 (0.0000477)	0**	0.03%
Electric Vehicle	0.188 (0.0695)	0.008**	20.7%
Income	0.000000564 (0.000000273)	0.041*	0.0000564%
PV_{logit}	0.156 (0.0848)	0.064*	17.2%
Occupancy	0.0428 (0.0281)	0.132^{+}	4.37%
Constant	8.23 (0.11)	0**	-

** p-value<0.01 , * p-value<0.1, $^{+}$ p-value<0.2

3.4. Instrumental Variable approach (IV)

A major complication that is emphasized in micro-econometrics is the possibility of inconsistent parameter estimation due to endogenous predictor variables. That is, OLS regression models might induce dependence between explanatory variables and regression errors. To further test the relevance of the discrete choice modeling approach in predicting electricity demand, I develop an instrumental variable model, as described in Equations 13 and 14. In the instrumental approach, the instruments Z are the variables that have the property that changes in Z are associated with changes in X but do not lead to changes in Y.

$$\log(Y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + \beta_{k+1} \widehat{\mathrm{PV}}_{IV,i} + \varepsilon_i \qquad \textbf{Equation 13}$$

$$\mathrm{PV}_{\mathrm{IV,i}} = \pi_0 + \sum_{j=1}^{k} \pi_j Z_j + v_i$$ **Equation 14**

where Yi represents annual electricity use (KWh)

Xi are the selected predictors of electricity demand

$\widehat{\mathrm{PV}}_{\mathrm{IV,i}}$ is the estimated outcome for household i to adopt solar PV

Zi represent the instrumental variables, so they are uncorrelated with the regression errors εi

$\mathrm{PV}_{\mathrm{IV,i}}$ are the observed indicators of PV adoption

βi and π_{i} are modeling coefficients and εi and vi are error terms

The IV approach results are shown in Tables 14a and 14b.

Table 14a: Instrumental Variable model results for annual electricity consumption, Step 1 (see Equation14).

IV Step 1: the instrumental variables are "Age of the home" and "Educational level"

Variable	Coefficient estimate	p-value	Variable Type
House Area (sf)	0.0000287 (0.0000483)	0.554	Exogenous
Income	$-2.43\text{x}10^{-08}$ ($2.75\text{x}10^{-07}$)	0.93	Exogenous
Occupancy	0.000573 (0.0246)	0.981	Exogenous
Electric Vehicle	0.0251 (0.0632)	0.692	Exogenous
Age of the home	-0.00561 (0.00124)	0**	**Instrumental**
Educational level (PostGrad)	0.0633 (0.0608)	0.3	**Instrumental**
Constant	0.881 (0.116)	0**	

** p-value<0.01 , * p-value<0.1, $^{+}$ p-value<0.2

Table 14b: Instrumental Variable model for annual electricity consumption, Step 2 (see Equation 13).

IV Step 2: Electricity demand prediction

Variable	**Coefficient estimate**	**p-value**	**% change in consumption for 1 unit increase in X variable**
$\widehat{\mathrm{PV}}_{IV}$	0.3899 (0.23)	0.091*	0.477
House Area (sf)	0.0002312 (0.000056)	0**	0.000231
Income	$7.47\text{x}10^{-08}$ ($2.99\text{x}10^{-07}$)	0.012*	$7.47\text{x}10^{-07}$
Occupancy	0.0612 (0.0265)	0.021*	0.0631
Electric Vehicle	0.1561717 (0.0693)	0.024*	0.169
Constant	8.07 (0.177)	0**	-

** p-value<0.01 , * p-value<0.1, $^{+}$ p-value<0.2

The Instrumental variable approach results indicate that age of the home and residents' educational level are relevant instrumental variables in that they are predicted to explain the difference in solar PV adoptions, without being correlated to the household annual electricity demand. Table 14a shows that an increase in the age of the house is predicted to decrease the chance of adopting PV. Results further demonstrate that PV adopters are estimated to consume roughly 48% more electricity, annually, than non-PV adopters (see Table 14b), which confirms the positive sign of the regression coefficient estimate corresponding to PV adoption in the DCM results (see Table 13).

However, I will not pursue the instrumental variable approach because of the lack of robust instrumental variables in our data set. I will, then, continue the analysis using the DCM framework.

3.5. Interactions Between PV as a Dummy Variable and Demand-Side Technologies

The installation of photovoltaic panels does not seem to be a significant predictor of electricity consumption when represented as a dummy variable (Table 8). We use the interaction terms shown in Equation 5 to estimate how consumers may leverage solar energy production for energy services.

We use the model in Equation 5 and a stepwise procedure to identify interaction terms that should be included in the final mixed model (Equation 15). The stepwise procedure tests whether the effect of installing photovoltaic panels on monthly electricity consumption depends on the adoption of other efficient technologies. The significant interactions included in the model test if electricity use for PV owners depends on the thermostat setting, home insulation efficiency or the number of Energy Star Appliances.

$$
\begin{aligned}
log(Y_{it}) = \\
\beta_0 + \beta_1 CDD_t + \beta_2 \frac{1}{\sqrt{HouseArea_i}} + \beta_3\, PV(dummy)_i + \beta_4\, InsulationR_i \\
+ \beta_5\, ESappliances_i + \beta_6\, ProgThermostat_i + \beta_7\, NumberDevices_i \\
+ \beta_8\, PV(dummy)_i \times ProgThermostat_i + \beta_9 PV(dummy)_i \times InsulationR_i \\
+ \beta_{10}\, PV(dummy)_i \times ESappliances_i + \beta_{11} R_i + \varepsilon_{it}
\end{aligned}
$$

Equation 15

Interaction terms describe joint installations of PV panels and specific end-use technologies. For example, electricity consumption may be influenced by homes with both PV and a programmable thermostat (PV x ProgThermostat = 1 x 1) differently than homes with just one technology. Interaction terms thus provide insight as to how homeowners appear to leverage production of onsite solar energy.

Margins plots of electricity demands are used to visualize the effect of interaction terms (e.g., joint technical change) relative to singular technical change by showing two distinct sources of technical change: one along the x-axis and one across the series. Figures 13 and 14 are examples of margins plots showing the effect of marginal change in thermostat efficiency and home insulation, respectively, and solar panel installation on electricity consumption.

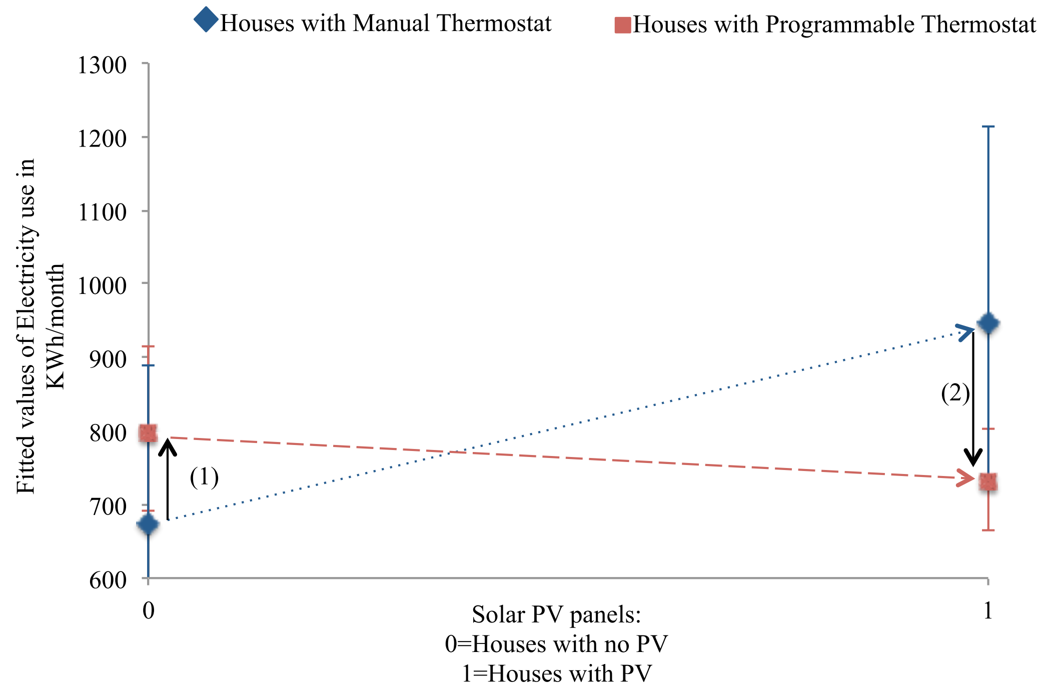


Figure 13: Margins plot showing the effect of marginal change in thermostat efficiency and solar panel installation on electricity consumption:

(1) For houses with no solar PV, those who have a programmable thermostat consume 40% more than houses with manual thermostats.

(2) For houses with solar panels, those who have a programmable thermostat consume 20% less than houses with manual thermostats.

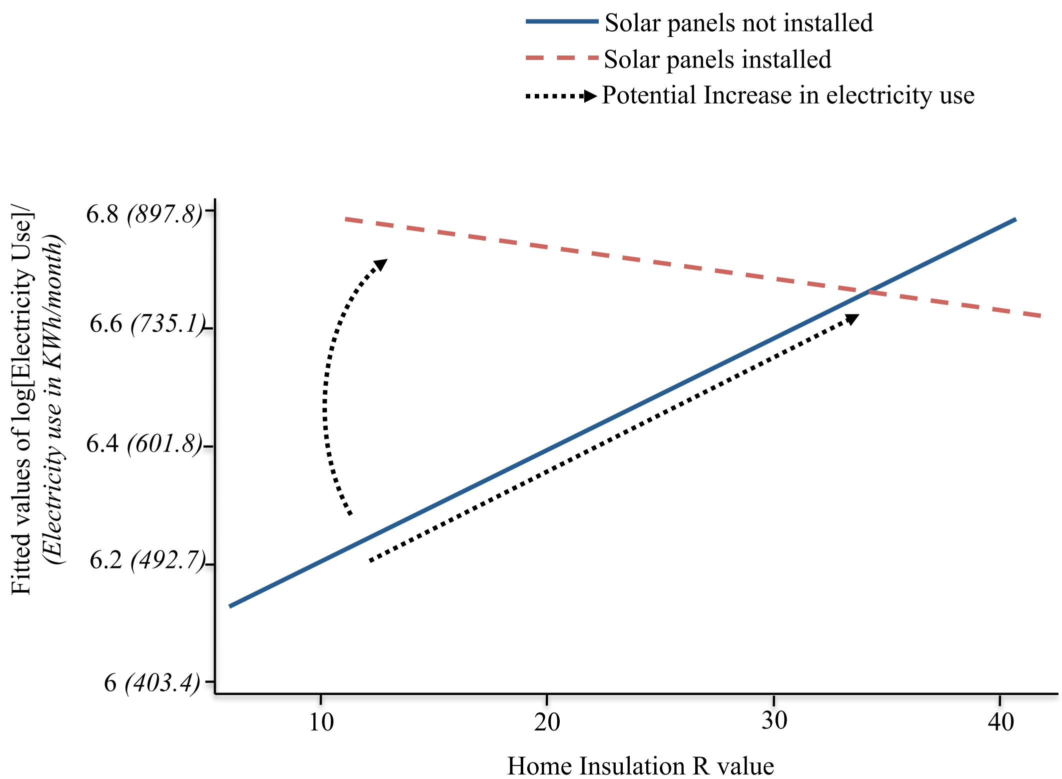


Figure 14: Margins plot showing the effect of marginal change in home insulation efficiency and solar panel installation on electricity consumption

Figure 13 indicates that homeowners without a programmable thermostat increase electricity use by 40% with the adoption of solar panels (arrow 1 in Figure 6). However, the combined effect of solar panels and a programmable thermostat leads to an approximate 20% decrease (Arrow 2 in Figure 13).

Similar results are depicted in Figure 14, where households without solar panels are predicted to consume more electricity, with increased insulation efficiency as shown by the positive slope (represented by the solid black line). It is evidence of rebound effect. In addition, homeowners with relatively inefficient insulation (R values less than 25) use more electricity when they adopt solar panels. Although these results do not show statistical significance, the lack of parallelism between the dotted line describing houses with solar panels and the solid line representing houses with no solar panels indicates that the effect of increasing insulation efficiency on electricity consumption depends on the adoption of solar panels. Further analysis of Figure 14 shows that homeowners achieve reductions in electricity use with a high level of insulation efficiency, averaging an R-value of 36.

Table 15 describes results of the full mixed model with interaction terms. The interaction terms included in the full model have the most explanatory power, but only one interaction is statistically significant. In fact, the impact of adopting photovoltaic technology on household electricity demand depends on the efficiency of the thermostat installed.

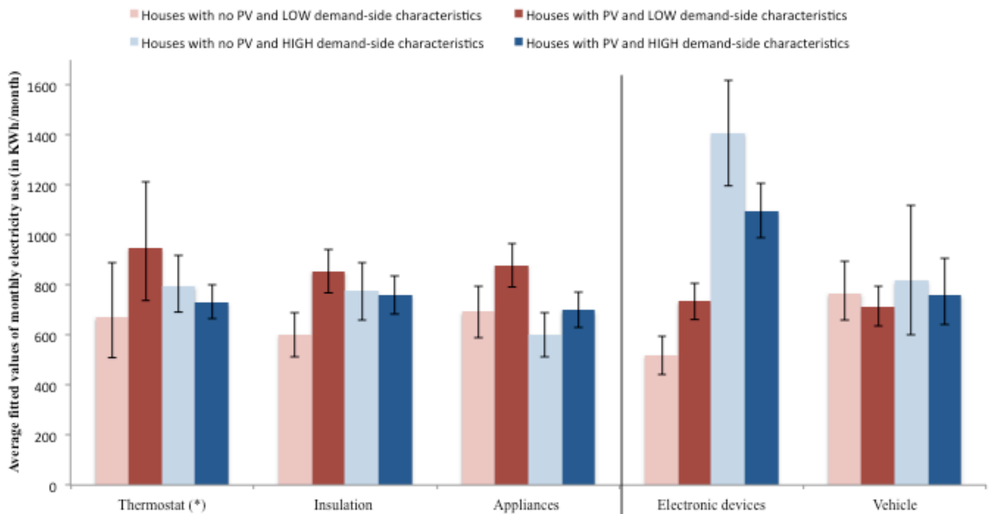
Table 15: Predictive mixed model for electricity consumption, with technology choice interactions (see Equation 5 in the text)

$$\log(Y_{elec}) = \beta_0 + \beta_1 CDD + \beta_2 S^{\lambda_1} + \sum_{j=1}^{5} \beta_j T_j + \sum_{\substack{j,z=1 \\ j \neq z}}^{3} \beta_j \, (T_j \, . T_{iz}) + \beta_i R_i + \varepsilon_{it}$$

Variables	**Coefficient estimate**	**Standard Error**	**z**	**P>lzl**
CDD= Cooling Degree Days	0.00125	0.0000457	27.5	< .0001
S_1= Floor area (in square feet) λ_1=-0.5	-68.9	12.05	-5.72	< .0001
ProgThermostat	0.1684	0.1515	1.11	0.266
Rvalue	-0.00538	0.00668	0.81	0.421
ESappliances	-0.0275	0.0646	-0.43	0.67
Devices	0.0211	0.00826	0.011	0.178
PV	0.663	0.341	1.95	0.052
ProgThermostat x PV	-0.429	0.195	-2.2	0.028 *
Rvalue x PV	-0.00853	0.00929	-0.92	0.358
ESappliances x PV	-0.09361	0.0899	-1.04	0.298
Constant	7.77	0.475	16.34	< .0001

Note: * Statistically significant interaction to the 10% level

Figure 15 shows similar results for five technology choices. While only one interaction term is significant (programmable thermostats and PV as described above), we include additional insignificant results because of the limited knowledge describing the observed performance of PV. Figure 15 indicates that homeowners owning at least one electric vehicle might use more electricity, but their consumption is slightly reduced when they adopt solar technology. Nevertheless, it should be noted that houses with no solar panels and low demand-side characteristics are predicted to be the lowest electricity consumers.



	Efficiency measures			New services	
LOW efficiency or new service adoptions	Non-Programmable	R value < 20	Number of Energy Star appliances < 1	Number of devices <5	Have No Electric vehicle
HIGH efficiency or new service adoptions	Programmable	R value > 30	Number of Energy Star appliances ≥ 2	Number of devices >20	Have at least one electric vehicle

Figure 15: Average monthly electricity consumption for houses with or without photovoltaic panels, across end-uses. Technology choices noted using (*) were statistically significant to the 10% level (see Table 8)

3.6. Interactions Between PV as a Discrete Choice and Demand-Side Technologies

I apply a similar methodology as described in the previous section to assess consumer response to energy savings from solar PV. However, I use the PV probability estimates from the discrete choice modeling framework (Equation 11) to control for the unobserved drivers of solar PV ownership. I screen for the most statistically significant interactions between the probability of installing solar panels and other efficient technologies and new services, including air conditioning units, insulation, windows, Energy Star appliances, electronic devices, and electric vehicles. Of the six investigated interactions, only one showed statistical significance: the interaction between PV adoption and Air conditioning efficiency rating (EER). Equation 16 describes the final annual electricity demand model with solar PV and Air conditioning efficiency interaction.

$$log(Y_i) = \beta_0 + \beta_1 HouseArea_i + \beta_2 ElectricVehicle_i + \beta_3 Income_i + \beta_4 Occupancy_i + \beta_5 \widehat{PV_{logit,i}} + \beta_6 AC\ Efficiency_i + \beta_7 \boldsymbol{\widehat{PV_{logit,i}}} \times \boldsymbol{AC\ Efficiency_i} + \varepsilon_i$$

Equation 16

Table 16 shows the regression results of annual electricity use described by Equation 16.

Table 16: Regression model for annual electricity consumption using PV discrete choice model (see Equations 11 and 16) Adjusted R^2= 0.4914

Explanatory variable	Coefficient estimate	p-value
House Area (square feet)	0.000301 (0.0000469)	0**
Electric Vehicle	0.215 (0.0712)	0.003**
Income	0.000000685 (0.000000272)	0.013*
PV_{logit}	1.29 (0.570)	0.026*
AC Efficiency	0.0705 (0.0412)	0.09*
Occupancy	0.0338 (0.0283)	0.234
PV_{logit} x AC Efficiency	**-0.103 (0.0513)**	**0.047***
Constant	7.44 (0.469)	0**

** p-value<0.01 , * p-value<0.1, $^+$ p-value<0.2

I use a contour plot of the variation in annual electricity use for all levels of air conditioning unit efficiency, with increased probability of the homeowner to install solar PV (see Figure 16).

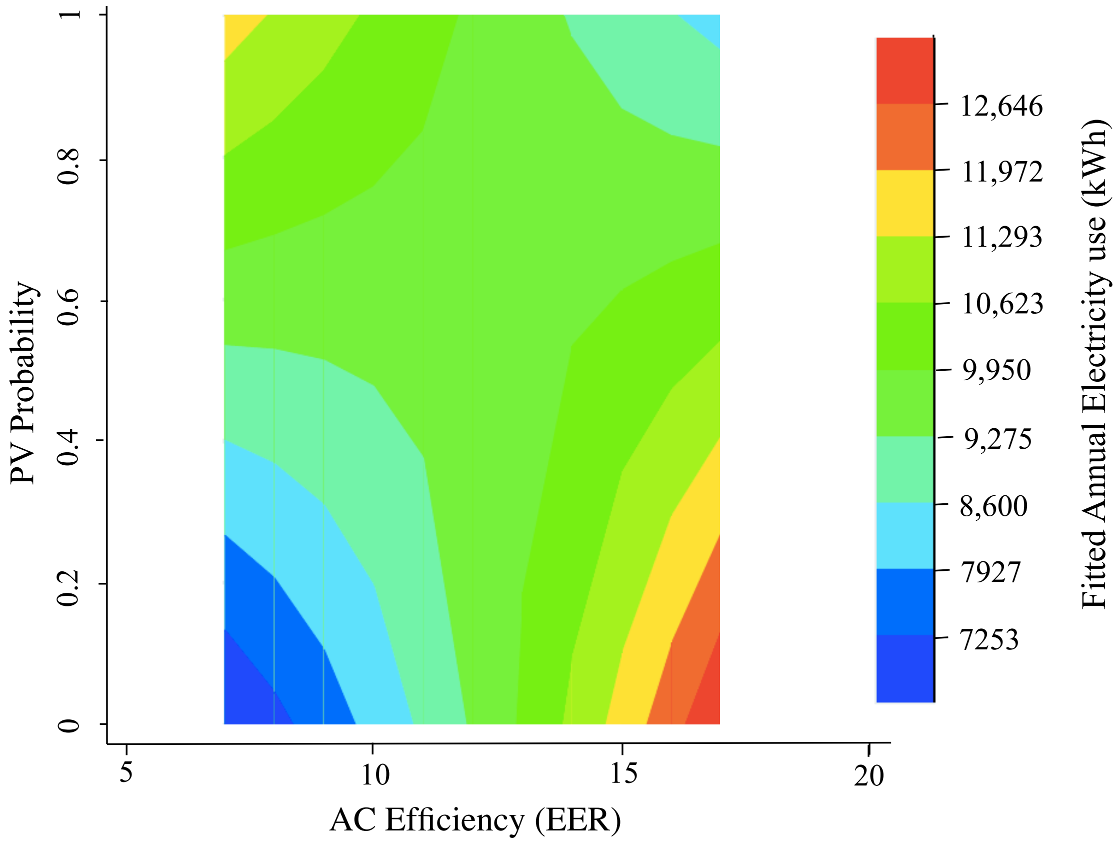


Figure 16: Contour Plot representing the predicted annual electricity use (in kWh) for the PV probability and AC Efficiency interaction

Results show that houses with a low probability of choosing to adopt PV technologies and a highly efficient air conditioning (AC) unit are the higher electricity consumers. In fact, within the set of houses with efficient AC units, households that choose to adopt PV panels are estimated to use nearly 38% more electricity than the non PV-adopting householders, annually. However, within the set of homes with an inefficient AC system, homeowners that choose to install solar panels are predicted to consume about 36% more than houses with no PV technology. The results further demonstrate that households with low efficiency ACs and no solar PV panels are predicted to be the lowest annual electricity consumers.

Therefore, the overall regression results suggest that sufficient consistent technical improvements, whether by adopting solar panels for houses with efficient AC units or installing more efficient AC systems for houses with solar PV, can lead to considerable annual energy reductions, estimated to be roughly 37%.

The empirical modeling results developed in this study are described in the following summary table (Table 17).

Table 17: Summary of findings from the combination of the discrete choice modeling exercise and electricity demand regression models.

Model #	Model Name	Model Type	PV Indicator Type	Specification Rationale	Major Findings
1	Monthly Electricity Demand	Mixed regression model of electricity use with household random effects (**Equation 3**)	Dummy coded (0,1)	Investigate the effect of seasonality on the performance of PV panels, using CDD	- The variation in CDD does not affect PV performance - PV installation is not statistically significant in explaining the variation in the household monthly electricity use
2	Annual Electricity Demand	Multiple regression model of electricity use (**Equation 4**)	Dummy coded (0,1)	Assess the differences in annual electricity use for PV and non-PV adopters	- PV installation is not statistically significant in explaining the variation in the household monthly electricity use
3	Electricity Demand with PV estimated choice preferences	Multiple regression model (**Equation 6**)	PV estimated choice preferences from DCM (**Equation 5**)	Assess the impact of household's choice to adopt PV on their annual electricity use	- Statistically significant factors that are predicted to drive PV installation include the individual's educational level, income, electric vehicle ownership, and age of the house. - Households that are more likely to adopt solar PV are expected to use on average 23% more electricity, annually.
4	Electricity Demand with PV estimated choice preferences	Multiple regression model (**Equation 7**)	PV estimated choice preferences from DCM (**Equation 8**)	Assess the impact of household's choice to adopt PV on their annual electricity use, by controlling for the unobserved factors of PV installation (DCM of electric vehicle adoption)	- Houses with higher occupancy are less likely to purchase an electric vehicle. - Houses with more conventional fossil fueled vehicles are more likely to own an electric vehicle. - Households that are more likely to adopt solar PV are expected to use on average 17% more electricity, annually.
5	Electricity Demand with DSM interactions	Mixed regression model with household random effects and DSM interaction terms (**Equation 10**)	Dummy coded (0,1)	Investigate how consumers leverage solar energy production for energy services	- Consumers might leverage the electricity gains from solar PV production towards space conditioning services, including the thermostat setting, insulation. - Sufficient energy efficiency improvements combined with solar technology installation could lead to the expected energy savings
6	Electricity Demand with DSM interactions and PV estimated choice preferences	Multiple regression model with household random effects and DSM interaction terms (**Equation 11**)	PV estimated choice preferences from DCM (Equation 8)	Investigate how consumers leverage solar energy production for energy services by controlling unobserved factors of solar PV adoption	- Consumers might leverage the electricity gains from solar PV production towards space conditioning services (air conditioning system). - Sufficient energy efficiency improvements combined with solar technology installation could lead to the expected energy savings

3.7. ESTIMATING THE "TAKE-BACK" EFFECT

Furthermore, I use the regression electricity model in Equation 10 to predict the magnitude of annual electricity use that is "taken back" from households that install solar panels. That is, I estimate what electricity consumption of the homes with PV panels would have been without PV installed. I will call these predicted values $\widehat{Y}_{\iota_{NO\ PV}}$ (See Table 13), and r_i the regression residuals:

$$\log\left(\widehat{Y}_{\iota_{NO\ PV}}\right) = 8.23 + 0.000292\times HouseArea_i + 0.188\times ElectricVehicle_i + 5.64\times10^{-7}\times Income_i + 0.0428\times Occupancy_i + r_i$$

Equation 17

I then estimate the predicted electricity consumption for the same houses with PV panels $\widehat{Y}_{\iota_{PV}}$ using Equation 10 (see also Table 13), as follows:

$$\log\left(\widehat{Y}_{\iota_{PV}}\right) = 8.23 + 0.156 + 0.000292\times HouseArea_i + 0.188\times ElectricVehicle_i + 5.64\times10^{-7}\times Income_i + 0.0428\times Occupancy_i + r_i$$

Equation 18

Figure 17 shows the distribution of $\widehat{Y}_{\iota_{PV}}$ and $\widehat{Y}_{\iota_{NO\ PV}}$.

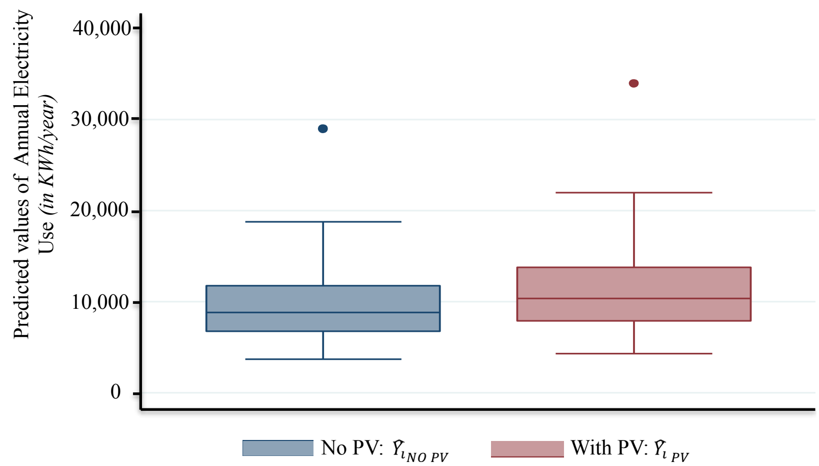


Figure 17: The distribution of the predicted electricity consumption for PV adopters, assuming PV or no PV installation, i.e. $\widehat{Y}_{\iota PV}$ and $\widehat{Y}_{\iota NO\ PV}$ respectively.

The distribution of the difference between the predicted consumption with and without PV- that we will call $\Delta\widehat{Y}_{\iota} = \widehat{Y}_{\iota PV} - \widehat{Y}_{\iota NO\ PV}$- can provide a rough estimate of the magnitude of the "take back" effect, or the amount of traditional grid energy that is not displaced but taken back towards consumption on site. In addition, I estimate the percentage of electricity "taken back" (i.e. $\Delta\widehat{Y}_{\iota}$), compared to the household electricity production from PV panels:

$$p_i = \frac{\Delta\widehat{Y}_{\iota}}{Z_i}$$

Equation 19

where: p_i is the "take-back" percentage, $\Delta\widehat{Y}_{\iota}$ represents the estimated electricity (in kWh/year) that was "taken back", and Z_i is the observed household electricity production from solar PV (in kWh/year). Figure 18 illustrates the distribution of the percentage of annual electricity production that was taken back and used on site consumption.

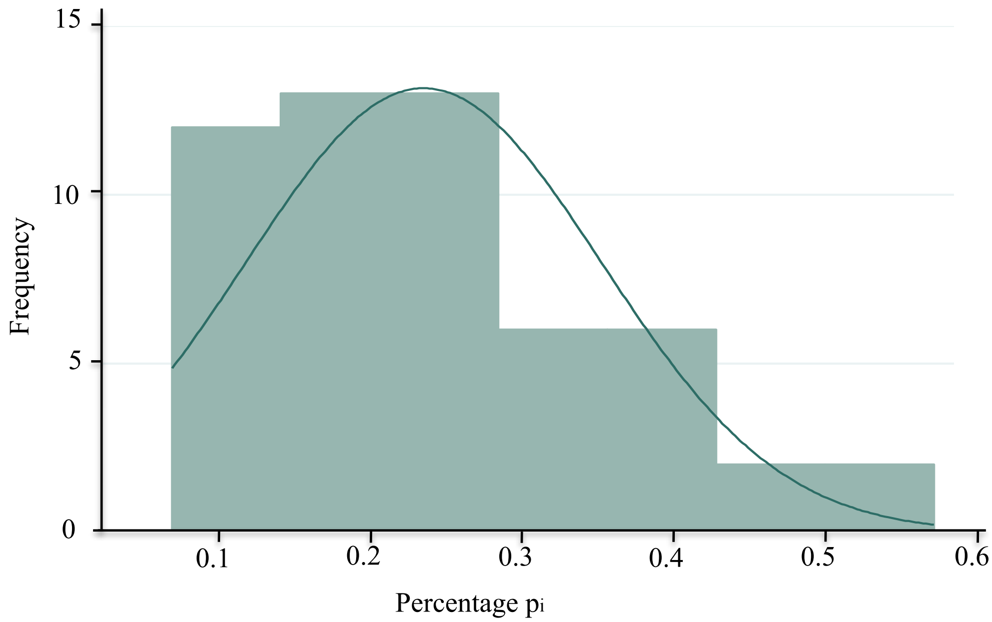


Figure 18: The distribution of the percentage of annual electricity production (i.e. p_i) that was taken back and used on site consumption (using Equation 19).

Figures 17 and 18 show that PV adopters are predicted to use roughly 1620 kWh/year more electricity than if they did not install solar PV. Results further indicate that this annual electricity amount that was "taken back" for other uses corresponds to almost 24% of the annual electricity production from PV panels, on average.

I further investigate the correlation between the percent annual electricity that was taken back by PV adoption, possibly for other on site consumption, and the capacity of PV panels. However, of the 214 households with metered PV electricity production, only 32 homeowners reported the PV capacities. Therefore, I estimate the panels capacity for the other 181 houses using both regression estimates and engineering calculations of PV capacity, based on the household electricity production from solar panels. I will refer to the predicted PV capacity from regression modeling as $\eta_{i,regress}$ and the calculated PV capacity as $\eta_{i,calc}$:

$$\eta_{i,regress} = \beta_0 + \beta_1 Z_i + \varepsilon_i$$

Equation 20

and

$$\eta_{i,calc} = \frac{Z_i}{\rho_i \times 0.77 \times 30.5 \times 12}$$

Equation 21

where:

β_0 and β_1 are the regression coefficients

Zi represent the observed annual electricity production from PV panels

ρ_i is the average solar radiation in kWh/m^2/day. For Texas, $\rho_i = 5.403$ kWh/m2/day

0.77 is the DC to AC Derate Factor (i.e. current conversion factor)

and 30.5×12 is the average number of days per year.

Figure 19 describes the percentage electricity taken back from PV installation (i.e. p_i) with increased PV capacity, for different household sizes.

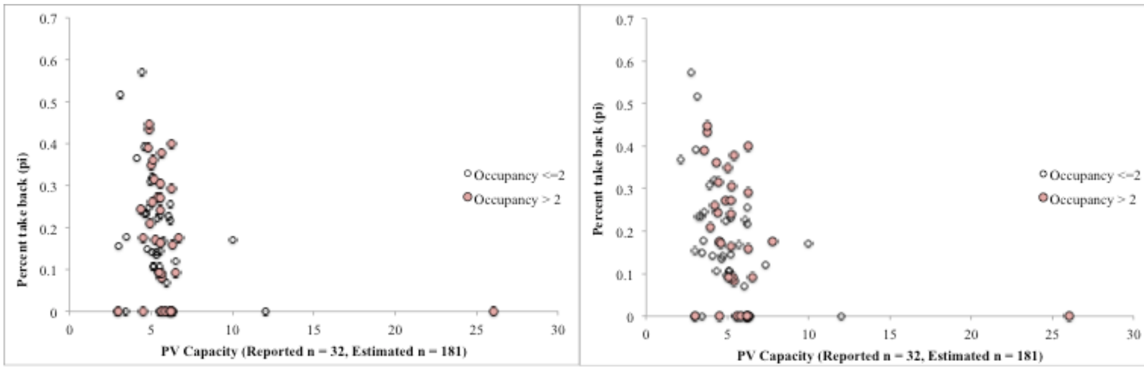


Figure 19: Percent electricity “taken back”, with increased PV capacity, for households with ≤ 2 occupants and > 2 occupants.

PV capacity values in the left chart (Figure 19) include reported values (sample siz=32) and estimated values from regression modeling as in Equation 20. PV capacity values in the right chart include reported values and estimated values from engineering calculations as in Equation 21.

Figure 19 shows no correlation between the amount of annual electricity “taken back” and PV capacity, regardless of the household size.

3.8. DISCUSSION

Policy makers and researchers have put tremendous emphasis on renewable energy and efficiency strategies to displace fossil fuel consumption [Lopez et al., 2012; EIA 2014]. Multiple studies have investigated the effectiveness of state and national incentives for increasing residential solar PV capacity [Cargo et al., 2014]. However, limited research on their empirical performance has been conducted. The existing studies are based on self-reported information and not on actual electricity consumption and technological choices. This study examines the impact of installing solar panels for efficient technology adopters on energy demand and investigates how consumers leverage their efficiency gains and solar energy productions. I also use a probabilistic discrete choice modeling framework to control for the unobserved factors that might drive consumer preferences in adopting "clean" technologies, including solar panels and electric vehicles.

The empirical results show no statistical significance of solar panel PV installation on household electricity consumption, when a dummy variable is used as an indicator of PV adoption. These results might seem surprising as consumers that choose to install rooftop PV panels are expected to have a higher level of "social responsibility", therefore reducing there energy use and displacing the "grid feed". These findings further support our initial intuit and show that consumer response to PV technologies depends on underlying behaviors that could offset the technically feasible energy savings. In fact, results further reveal that PV adoption probability estimates (using the discrete choice modeling results) are correlated with household electricity demand and that PV adopters in our sample consume about 30% more electricity than non-adopters. This is not entirely surprising since solar panels demonstrate nearly free long-run operating costs, and grid-connected homes have access to an affordable source of energy. In addition, nearly 90% of market PV costs were provided as subsidies to participants purchasing PV panels [Pecan Street 2013; Feldman et al. 2013]. However, our data is purely cross sectional and do not provide the times when consumers adopted solar technologies. Therefore, the study results could indicate that households with high electricity use purchased PV panels in the context of "charitable giving" [Rose-Ackeman, 1982]. The PV adopters, who could also be high electricity consumers, might feel that they decreased some of the disutility associated with increased consumption. By purchasing solar technologies, these consumers feel as they "bought in" and have done their part [Jacobsen et al., 2010], which does not ensure reductions in household electricity use, in the long run.

These results might also be specific to the typology of our sample and may not be representative of the long-run photovoltaic technology performance, as most of PV adopters received high incentives to purchases their solar panels. Further quantitative research should be carried out to better understand the role of residential solar productions in policymaking.

Discrete choice modeling results indicate that PV adoption is affected by multiple factors including household educational level, income and electric vehicle ownership. The latter conclusion is not surprising as consumers that would purchase an electric vehicle are more likely to adopt other "environmentally friendly" technologies. However, the discrete choice modeling analysis of the drivers of electric vehicle ownership imply that consumers who own multiple conventional fossil fuel vehicles are more likely to purchase an electric vehicle. These findings suggest that affluent consumers might purchase electric vehicles in addition to conventional gas fueled vehicles. That is, the consumers that choose to buy an alternative fuel vehicle might not use it as their primary means of transportation, but an extra vehicle because they can afford it. Therefore, electric vehicle ownership cannot serve as a robust proxy for the "environmental consciousness" of the study population that actually represent a more affluent fraction of US households. More empirical research with a diverse, cross-sectional sample is needed to better understand the net economic and environmental effect of electric vehicles and solar PV adoption.

Finally, consumers that adopt solar panels are faced with three choices on how to use energy gains from PV production; displace conventional electricity use, utilize all or part of the energy gains for conventional end-uses (e.g. space conditioning technologies), or use them for new services (e.g. electronic devices). The analysis of PV panel annual electricity production that was taken back, possibly for on-site consumption, implies that households with PV technologies might use almost 24% of the electricity generated for other uses. Furthermore, the study results indicate that this "take-back" percentage is independent of the rated power of the panels. These findings suggest that perhaps homeowners have some awareness of the limits of the panels, as we would have expected that the take back effect would be higher for panels with lower ratings.

I use regression interaction terms to investigate how consumers' might leverage the "free" generated energy from solar panel adoption. In fact, the empirical results show that households use part of the energy gains for additional home cooling or heating, probably for enhanced physical comfort. These results further reinforce the problematic question of the impact of technologies, including solar panels and efficiency measures, in possibly promoting higher electricity consumption. The consumers might feel "morally licensed" to use part of the energy gains from PV production towards other end-uses and services [Jacobsen, 2010; Miller and Effron, 2010]. However, results also suggest that consumers can achieve the expected energy reductions with sufficient and consistent technical improvements. For example, houses with both solar panels and efficient air conditioning system are predicted to consume about 35% less than houses with solar panels only but inefficient AC units, or an efficient AC unit but no solar PV. Households would need to achieve a "minimum level of efficiency" to ensure that the behavioral response to technology adoption does not offset its benefits. This "minimum level of efficiency" can be defined as the combination of DSM strategies and solar installation, or a bundle of multiple end-uses and services. Therefore, program implementers and private utilities should foster efforts to design these bundles, based on customized household energy audits. Further empirical investigation on the implications of policy interventions and public support on both solar PV installations and energy consumption should be carried on, in order to better define the behavioral drivers of energy use patterns, upon the adoption of solar technologies.

4. Combining Rehabilitation and Retrofitting Strategies to Maintain the Location and Use of the Texas Multifamily Affordable Rental Properties

US households have increasingly turned to the rental market for housing, thus changing the long-term homeownership trends. The demand for rental housing has particularly increased with the Echo Boomers (born 1977-1995) and Baby Boomers (born 1946-1964) who value the flexibility, urban life, and freedom from ownership responsibilities. The US renter share rose from 31% in 2004 to 35% in 2012, reaching a total number of 43 million by early 2013 [Harvard Kennedy School, 2013]. Further demographic change is expected to generate 4.7 million more renter households by 2023 [JCHS, 2014]. Renter-occupied housing stock provides a broad array of housing choices, including multifamily houses that represent 42% of the rental market [Harvard Kennedy School, 2013].

Over 30% of the U.S. population and over 25% of U.S. households live in multifamily buildings [Benningfield, 2009]. Although the housing market is in gradual recovery and it has taken 7 years for employment rates to achieve the pre-recession levels, the US multifamily rental market is robust and expected to remain strong throughout most of the country. The development of multifamily housing projects in cities such as Austin, Seattle, Denver, and Washington, D.C. continues to grow, mainly due to increasing employment rates and positive net migration trends [FannieMae, 2014]. From 1950 to 2010, the population more than tripled in the state of Texas, which was practically non-existent in terms of multifamily housing construction until about 50 years ago. Since then, Texas metropolitan areas recorded some of the highest development growth nationwide. The city of San Antonio built more than 32% of its current multifamily housing stock between 2000 and 2011 [FannieMae, 2014].

The demand for affordable rental housing continues to rise. The U.S. Department of Housing and Urban Development (HUD) defines a unit as affordable if the gross rent (rent plus tenant-paid utilities) is no more than 30 percent of the household's income. In 2005, 25% of renter households nationally spent more than half their income on housing [JCHS, 2007]. In Florida, for example, almost two out of three low-income renter households spend more than 40% of their income on rent [Shimberg Center for Affordable Housing, 2008]. It is therefore more challenging today to ensure that the rising supply of affordable multifamily residences meets the demand for multiple reasons; an increasing number of renters; elevated unemployment and underemployment; stagnant incomes; rising rents; and increasing construction costs. [FannieMae, 2014].

Across the nation, state and local government entities have combined their efforts to identify effective strategies to provide affordable housing and homeownership opportunities to low-income families. The US Department of Housing and Urban Development (HUD) provides project-based multifamily programs aimed at assisting and funding low-income housing properties that are privately owned. These HUD-assisted programs, created in the 1960s and 1970s, provide subsidies to private owners in exchange for serving low-income tenants, which led to the development of almost 1.5 million units [HUD, 2006]. HUD requires certain conditions on the assisted properties, including restrictions on the tenants' income and the rent values that the owners may charge. Approximately 2.3 million US households live in 31,240 apartment buildings that are privately owned and subsidized by HUD [Bomberger, 2010]. But these assisted multifamily programs are distinct from the public housing programs that develop and operate publicly owned properties. HUD programs are aimed at promoting the development of privately owned affordable housing [HUD, 2006].

Nevertheless, HUD-assisted properties are disappearing from the affordable housing stock and low-income tenants are displaced due to expirations of affordability restrictions and tenants' rent assistance [Shimberg Center, 2008]. Affordable multifamily properties can be lost to deterioration and default, especially in distressed neighborhoods. In particular, many properties built during the 1960s through 1980s are physically deteriorated due to deferred capital improvements but owners have no or limited capital reserves [Khadduri and Wilkins 2007; Wilkins 2002]. The American Community Survey conducted by the U.S Census Bureau found that roughly 60% of U.S. rental properties with 20 or more units were built before 1980, with more than half of the affordable low-income properties being at least 50 years old. Furthermore, given the ongoing increase in demand for multifamily affordable rental housing, a significant and sustained gap could appear between the supply and demand of low-income housing. Local housing authorities cannot rely solely on new construction to fill this gap. Therefore, additional efforts should be directed toward renovating, preserving, and, retrofitting the nation's aging rental-housing stock.

Private funding sources such as banks and private financial entities usually focus on properties with high market values and do not provide appealing funding options to older, more distressed rental housing. Therefore, these owners of affordable multifamily properties have greater challenges attracting private capital. Renovation practices and efficiency enhancements could help preserve not only the units themselves, but also the subsidies, such as Low-income Housing Tax Credits (LIHTC) and rent assistance, that maintain the affordable status for low-income renters.

Furthermore, the United States has emphasized the importance of achieving more environmentally friendly building stock across all sectors. In this context, it is important to identify the sectors that have a potential for energy savings. As the U.S. multifamily housing stock is relatively older than the single-family stock [Benningfield Group, 2009], it should have a higher potential for energy and water use reduction. U.S. multifamily properties spend roughly 31 billion dollars on energy [National Energy Technology Lab, 2009].

Despite the uncertainties on the performance of demand-side strategies, the US public entities and private utilities still count upon energy efficiency and renewable resources to achieve predicted social and environmental benefits, and increase consumer welfare. However, “measurement and verification” methods do not ensure that the monetary benefits resulting from DSM and renewables are not re-spent or eroded, possibly due to behavioral phenomena (e.g. “rebound effect”). Therefore, a reasonable way to utilize these benefits could be retrofitting low-income multi family housing units that might be displaced because of increasing costs in the real estate market. The enhancement of energy and water performance for multifamily rental housing properties could help reduce energy and water costs, improve the tenants’ comfort, increase the property value, reduce building maintenance, and extend the life of the building. Previous studies estimated that investing 46 billion dollars between 2009 and 2020 to unlock energy efficiency opportunities in U.S. low-income buildings could provide almost 16 billion dollars in reduced utility expenditures the multifamily sector [McKinsey & Company, 2009].

Although multiple studies have attempted to quantify the predicted energy saving potential from the US multifamily housing market [McKinsey & Company, 2009; Benningfield Group, 2009; HUD 2011; Greely et al., 1986], subsector and locally specific analyses of the cost and benefits from implementation of energy and water conservation measures, in addition to building renovation, have not been well documented.

This study provides an engineering economic model of rehabilitation and energy and water retrofitting costs for affordable multifamily rental housing units located in Austin, TX. The purpose of this work is to prioritize policy interventions aimed at maintaining property location and use, and to identify the capital investment needs that could be partially provided by the U.S. Department of Housing and Urban Development (HUD). In particular, this study investigates the potential outcomes generated from the decision-making process of a property owner by considering financial incentives to renovate and implement energy and water retrofits for existing, low-income multifamily rental buildings.

4.1 MATERIAL AND METHODS

This study evaluates costs and benefits of rehabilitating and retrofitting low-income multi-family housing units in Texas. The costs considered in this analysis include building rehabilitation costs along with costs of replacing existing inefficient building-related technologies, including energy and water consuming equipment (e.g. air conditioning systems, appliances, etc.) and other measures that influence energy and water consumption (e.g. windows). I also include the costs of installation of rooftop solar photovoltaic (PV) panels as a source of distributed electricity generation. Benefits comprise the energy and water use reductions that are generated from using efficient technologies, in addition to the electricity production from solar PV.

I limit the technologies considered in this study to lighting, residential appliances, space heating and cooling equipment, envelope-related systems, domestic hot water, and solar PV panels. Residential appliances include refrigerators, freezers, and dishwashers. Space heating and cooling equipment are limited to furnaces and air conditioning units, respectively, and do not include heat pumps, as most of the houses in Texas use natural gas as the primary source of heating. I also consider envelope-enhancing measures such as ceiling insulation, wall insulation, and efficient windows.

4.2 Baseline Energy and Water Consumption

I first apply regression models to the Residential Energy Consumption Survey (RECS, 2009) to estimate the baseline energy and water consumption for multifamily homes. RECS contains 1,923 multi-family dwelling observations, with about 900 reported survey values including building characteristics, household information, appliances and energy consumption. Table 18 describes the data fields that were analyzed in this study.

Table 18: Summary statistics of the explanatory variables used in the analysis

Category	Variable	Mean and Standard Deviation (RECS, 2009)
Climate	Heating degree days (per year)	Mean= 3853; s = 2260
	Cooling degree days (per year)	Mean= 1454; s = 1184
Structural factors (S)	Unit area (square feet)	Mean= 858; s = 333
	Number of rooms per unit	Mean= 3.62; s = 1.29
	Number of floors in the building	Mean= 3.86; s = 4.38
	Number of apartments/units per floor	Mean= 1.07; s = 0.277
	Building vintage	Mean= 41.6; s = 22.9
	Rented units	Proportion=87%
	Number of Windows	< 5: 61% > 5: 39%
	Type of Windows	Single pane: 55% Double and Triple pane: 45%
Demographic factors (D)	Household members (Occupancy)	Mean= 2.03; s = 1.25
	Average age of the tenants	Mean= 44.9; s = 18.8

Table 18 continued:

Space Conditioning Equipment (SC)	Steam or Hot Water System	Proportion=20%
	Central Warm-Air Furnace	Proportion=58%
	Natural Gas as the heating fuel	Proportion= 36.6%
	Electricity as the heating fuel	Proportion= 54.1%
	Natural Gas as the cooling fuel	Proportion= 64.2%
	Electricity as the cooling fuel	Proportion= 35.7%
	Heating Equipment age	< 10 years: 43% 10 to 20 years: 26% > 20 years: 31%
Water Heating (WH)	Natural Gas as the water heating fuel	Proportion= 45.3%
	Electricity as the water heating fuel	Proportion= 49.6 %
Energy	Annual Electricity Consumption per dwelling unit (KWh/year)	Mean= 6414; s = 4072
	Annual Natural Consumption per dwelling unit (kBTU/year)	Mean= 21884; s = 13895

I develop multiple regression models of electricity and natural gas consumption to investigate the household and building characteristics that influence annual energy use and identify adequate retrofits that could ensure energy use reductions and monetary savings. I use stepwise regression and purposeful screening techniques to develop Equations 22 and 23 that show regression models for electricity and natural gas consumption for multifamily housing units in the RECS data. Model results are presented in the Supplemental Information (SI-Tables 1 and 2).

$$log(Y_{elec,i}) = \beta_0 + \beta_1 HDD_i + \beta_3 CDD_i + \beta_4 CensusRegion_i + \sum_{k=5}^{11} \beta_k \times S_{k,i} + \sum_{k=12}^{14} \beta_k \times D_{k,i} + \sum_{k=15}^{18} \beta_k \times SC_{k,i} + \beta_{19} \times WH_i + \varepsilon_i$$

Equation 22

$$log(Y_{NG,i}) = \beta_0 + \beta_1 HDD_i + \beta_3 CDD_i + \sum_{k=5}^{9} \beta_k \times S_{k,i} + \sum_{k=10}^{12} \beta_k \times D_{k,i} + \sum_{k=13}^{16} \beta_k \times SC_{k,i} + \beta_{17} \times WH_i + \varepsilon_i$$

Equation 23

where: $Y_{elec,i}$ represents the annual electricity consumption observations in KWh

β_k are the regression coefficient estimates for fixed effect

HDD_i and CDD_i represents Heating and Cooling Degree Days, respectively

$S_{k,i}$ represents the series of household structural factors described in Table 18

$D_{k,i}$ represents the series of household demographic factors described in Table 18

$SC_{k,i}$ represents the series of space conditioning equipment factors described in Table 18

WH_i represents the fuel used in water heating including electricity and natural gas

ε_{it} represents the error terms

Regression results of annual electricity use (see Equation 22 and SI-Table 1) show that built-in electric units and heat pumps account for 44.5% of space conditioning electricity use. Results further demonstrate that space heating equipment that is older than 10 years consume roughly 24% more electricity than newer heating units. Rental multi family apartments are also estimated to consume 8% more than owned units.

Regression results from Equation 23 show that houses with double or triple pane windows decrease annual natural gas use by 11% and 20%, respectively, compared to households with single pane windows.

To determine the baseline water consumption for multi family households, I use a regression model that was developed by William B. DeOreo and Matthew Hayden (2008). The water demand model is described by the following regression equation (Equation 24).

$$\log\,(CCF\ water\ use)_i = \beta_0 + \beta_1 Occupancy_i + \beta_2 Clothes\ Washer_i + \beta_3 Irrigation_i + \beta_4 Vintage_i + \epsilon_i$$

Equation 24

where CCF water use represents annual household water use (in 100's of cubic feet), β_j are regression coefficients, and ϵ_i are the model error terms.

The regression coefficient estimates are presented in Table 19, where the multifamily units were disaggregated into groups, indicating the house vintage, whether they own a clothes washer or use irrigation systems.

Table 19: Models for predicting annual water use (ccf) in multi-family units [DeOrea, 2008]

Group Name	**Model Equation**
Apartments with Clothes washer	$49.09 * \text{Occupancy}^{0.4}$
Apartments without a Clothes washer	$39.59 * \text{Occupancy}^{0.44}$
Condos with Irrigation and built before 1995	$55.4 * \text{Occupancy}^{0.56}$
Condos with Irrigation and built after 1995	$43.76 * \text{Occupancy}^{0.56}$
Condos without Irrigation and built before 1995	$45.41 * \text{Occupancy}^{0.56}$
Condos without Irrigation and built after 1995	$35.9 * \text{Occupancy}^{0.56}$

Based on analysis of the RECS energy consumption data (Equations 22 and 23) and the water use estimates (Equation 24), I determine the baseline energy and water use and costs for multi family properties, as shown in Table 20.

Table 20: Annual property energy and water use and cost

	Use/ft^2	**Use/Unit**	**Cost/ft^2**	**Cost/Unit**
Energy use	60.9 kBtu/ft^2/year	46,214 kBtu/unit	$1.49	$1,151
Water use	55.4 Gal/ ft^2/year	117 Gal/unit/day	$0.30	$232
Total			**$1.67**	**$1,293**

Results indicate that on average, multifamily properties spend roughly $1,151 per unit on energy and $232 per unit on water annually. Therefore, a 50-unit property spends $57,650 on energy and $11,600 on water annually. If this property saved 15% on energy and water costs, it would increase the asset value by almost $160,000, assuming a 6.5 % capitalization rate.

The least efficient properties (those in the 95th percentile) in the RECS data use over three times as much energy per square foot and two times as much water per square foot as the most efficient properties (those in the 5th percentile). In addition, for a sample

50-unit property, this translates to a difference in energy cost of $69,150 annually, which is a substantial monetary expenditure. Figures 20 and 21 illustrate the distribution of energy and water use per square foot and per unit across the properties in our analysis.

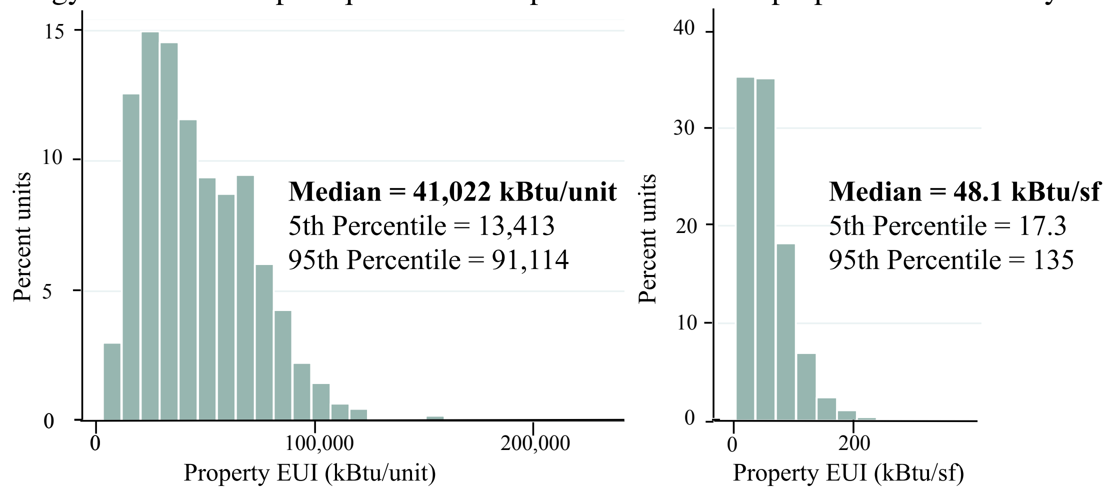


Figure 20: Distribution of the whole property energy use

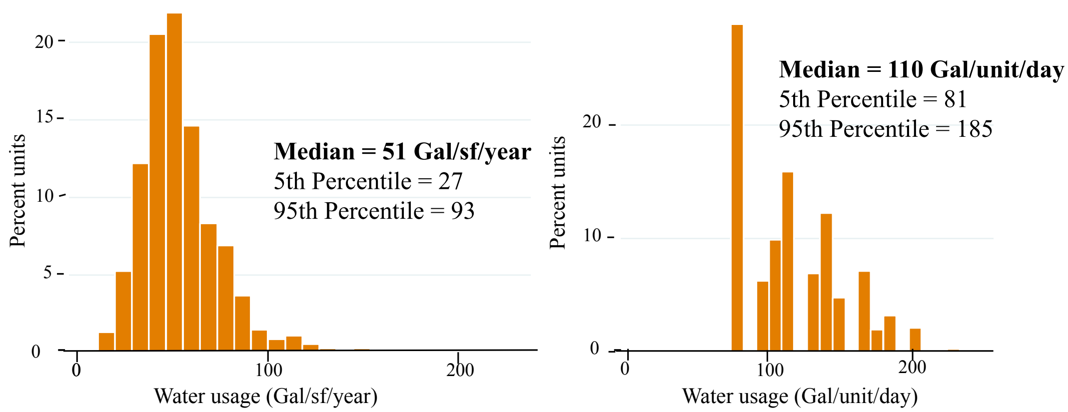


Figure 21:Distribution of the whole property water use

4.3. Rehabilitation Costs

The Low-Income Housing Tax Credit (LIHTC) has been the major mechanism for supporting the production of new and rehabilitated rental housing for low-income households since its creation in 1987, as part of the Tax Reform Act (TRA). The LIHTC program offers incentives to private investors to provide equity for affordable rental housing, by guaranteeing tax credits to those investors [Cummings, 1998].

The LIHTC database, created and released by the US Department of Housing and Urban Development (HUD) in 1997, contains information on 39,094 projects and almost 2,458,000 housing units placed in service between 1987 and 2012 [HUD 2012]. The database includes project address, number of units and low-income units, number of bedrooms, year the credit was allocated, year the project was placed in service, type of project (i.e. new construction or rehabilitation), type of credit provided, and other sources of project financing [HUD 2012].

The data describing rehabilitation and new construction costs for low-income multi-family (MF) houses were obtained from the LIHTC database. I limited the analysis to multifamily affordable rental housing projects located in Texas, which reduced the sample size to 40 rehabilitation and 151 new construction projects that were placed in service between 1995 and 2010.

I use the LIHTC data to estimate the development costs for affordable multi-family houses, for both rehabilitation and new construction projects. As these projects were placed in service between 1995 and 2010, I use the RSMeans historical cost of construction indexes (see SI –Table 3) to estimate the time-adjusted costs (Equation 25).

$$\frac{Index\ of\ Year\ 2014}{Index\ of\ Year\ A} \times X_A = X_{2014} \qquad \textbf{Equation 25}$$

where X_A is the total development cost when the project was placed in service and X_{2014} is the time-adjusted total development cost for the same project in 2014. I account for uncertainties in the estimated total development costs of new construction and rehabilitation projects using Monte Carlo Simulations. Table 21 describes the characteristics and total development costs for rehabilitation and new construction projects in the study sample.

Table 21: Distribution of Development costs for rehabilitation and new construction projects

	Rehabilitation		**New Construction**	
	Average	*Standard Deviation*	*Average*	*Standard Deviation*
Number of projects in the sample	40	-	151	-
Number of units	122	96	140	74
Number of low-income units	119	93	134	74
Development Costs per unit ($2014)	**$31,391**	$17,396	**$147,427**	$84,000

Comparing all the ranges of costs per unit, it is clear that the cost of replacement of multi-family properties would exceed that of comprehensive rehabilitation (see Table 21). The cost for the HUD to replace its housing stock in-kind considerably exceeds the cost of rehabilitation on average by a factor of at least 300%. The order of magnitude of the average cost estimate for replacement exceeds the entire range of costs for rehabilitation at a minimum of 123% greater, but could range up to over nine times costlier.

4.4. Retrofit Measures

Retrofit strategies proposed in this study include energy and water efficiency measures as well as solar PV panels, aimed at reducing residential energy and water consumption. These technologies are characterized by their capital cost, installation costs (i.e. labor costs), service life, and impact on energy and/or water consumption.

The retrofit measures considered in this analysis are described in Table 22.

I use data from the California Database for Energy Efficient Resources (DEER) that has been developed by the California Public Utilities Commission (CPUC 2005). This database provides well-documented measure costs and effective useful life (EUL) for selected energy efficient technologies. In addition, the DEER estimates *ex-ante* energy and peak demand savings using the latest DOE-2 simulation engine via eQUEST, a sophisticated, building energy use analysis tool.

Table 22: Description of the twenty-one energy and water retrofit measures included in the analysis.

(The table provides information on the efficiency level of the existing (inefficient) and efficient technologies, along with the data sources. Market trend data consist of compiled information on efficient products that are widely used in the residential market.)

Measure Category	***Retrofit Stock***	***Existing stock description***	***Efficient stock description***	***Data Sources***
Lighting	Lighting	Incandescent lighting fixtures	CFL and LED fixtures	Market trends
Appliances	Refrigerator	Standard Refrigerator	ENERGY STAR Refrigerator	ENERGY STAR, market trends
	Freezer	Standard Freezer	ENERGY STAR Freezer	ENERGY STAR, market trends
	Dishwasher	Standard Dishwasher	ENERGY STAR Dishwasher	ENERGY STAR, market trends
HVAC	AC replacement	Standard Efficiency System	AC system with 14.0 SEER	DEER database
	Furnace	Standard Efficiency System	Condensing 90 AFUE Furnace	DEER database
	Whole house fan	No Night Ventilation/Economizer	Night ventilation	DEER database
	Programmable Thermostat	No night setback/setup	Programmable thermostat	DEER database
Envelope	Duct Sealing	Total Leakage > 30%	Reduce total duct leakage by at least 50%	DEER database
	Ceiling Insulation	Ceiling R-0	Ceiling R-value > 30	DEER database
	Window screen	No window screens	Window Screens with Shading Coefficient of less than or equal to 0.87	DEER database
	Window film	No window films	Window Film with Shading Coefficient of less than or equal to 0.87	DEER database
	Air Sealing Improvements	No Air Sealing	Perform weatherization, stripping, caulk, etc. to home	DEER database
	Windows Replacement	Standard single pane windows	Windows with Solar Heat Gain of less than 0.65	DEER database
	Wall Insulation	Existing wall insulation	Insulate walls to R-8 or higher	DEER database
Domestic Hot Water	Faucet aerator	Standard faucet flow = 2.5 gpm	Faucet flow less than or equal to 1.5 gpm	Market trends
	Showerheads	Standard shower flow = 2.5 gpm	Low Flow Showerheads to decrease flow to less than or equal to 2.0 gpm	Market trends
	Domestic Water Heater-NG	Standard NG Water Heater	High Efficiency NG Water Heater with a Minimum Efficiency of 0.90	DEER database
	Domestic Water Heater-Electric	Standard Electric Water Heater	High Efficiency Electric Water Heater with a Minimum Efficiency of 0.90	DEER database
	Pipe insulation	No Pipe Wrap	Insulate walls to R-8 or higher	DEER database
Renewable technologies	Solar Photovoltaics	Solar PV panels	No Solar panels	Market trends

Equations 26 and 27 show the costs and benefits per household, for each energy and water conservation measure, also referred to as "End-Use Stock".

$$Cost\ NPV_{End-use\ Stock} = (Capital\ Cost + Labor\ Cost) \times N \times Percent_{penetration}$$

Equation 26

$$Benefit\ NPV_{End-use\ Stock} = \left(e_{savings} \times P_e + n_{savings} \times P_{NG} + w_{savings} \times P_{water}\right) \times \frac{1-(1+i)^{-n}}{i \times (1+i)^n} \times N \times Percent_{penetation}$$

Equation 27

where N is the quantity of end-use stocks per dwelling unit, $Percent_{penetration}$ is the penetration rate of the end-use stock, $e_{savings}$, $n_{savings}$, and $w_{savings}$ are the annual electricity, natural gas, and water savings resulting from the installation of the efficient end-use stock, i is the discount rate, and n is the stock service life.

There are six sources of uncertainty in our model: unknown quantities of stocks, capital costs, labor costs, energy and water demands, service life, and market discount rate.

This uncertainty comes from the lack of accurate data or multiple sources that describe these end-use stocks. Therefore, I control for the unknown variability by creating a normal distribution for these input variables, using the minimum and maximum values (see Appendix C). In addition, the input assumptions used to estimate the NPV of costs and benefits are given in Table 23.

Table 23: Input assumptions used for the Monte Carlo Simulation

Parameter	Unit	Min	Max
Household Size (per unit)	Members	1.19	2.88
Discount rate	%	0.03	0.05
Price of Water	$2014/kGal	5.21	5.69
Price of Electricity	$2014/kWh	0.118	0.123
Price of Natural Gas	$2014/kBtu	0.0145	0.0167
% of households with electric water heater	%	0.46	0.80
% of households with natural gas water heater	%	0.30	0.60
Population Multiplier	%	0.9	1
Number of dwelling units per building	Units	14	152

The Monte Carlo simulation results for the energy reductions and net present value of the proposed energy and water efficient stock are described in Figure 22.

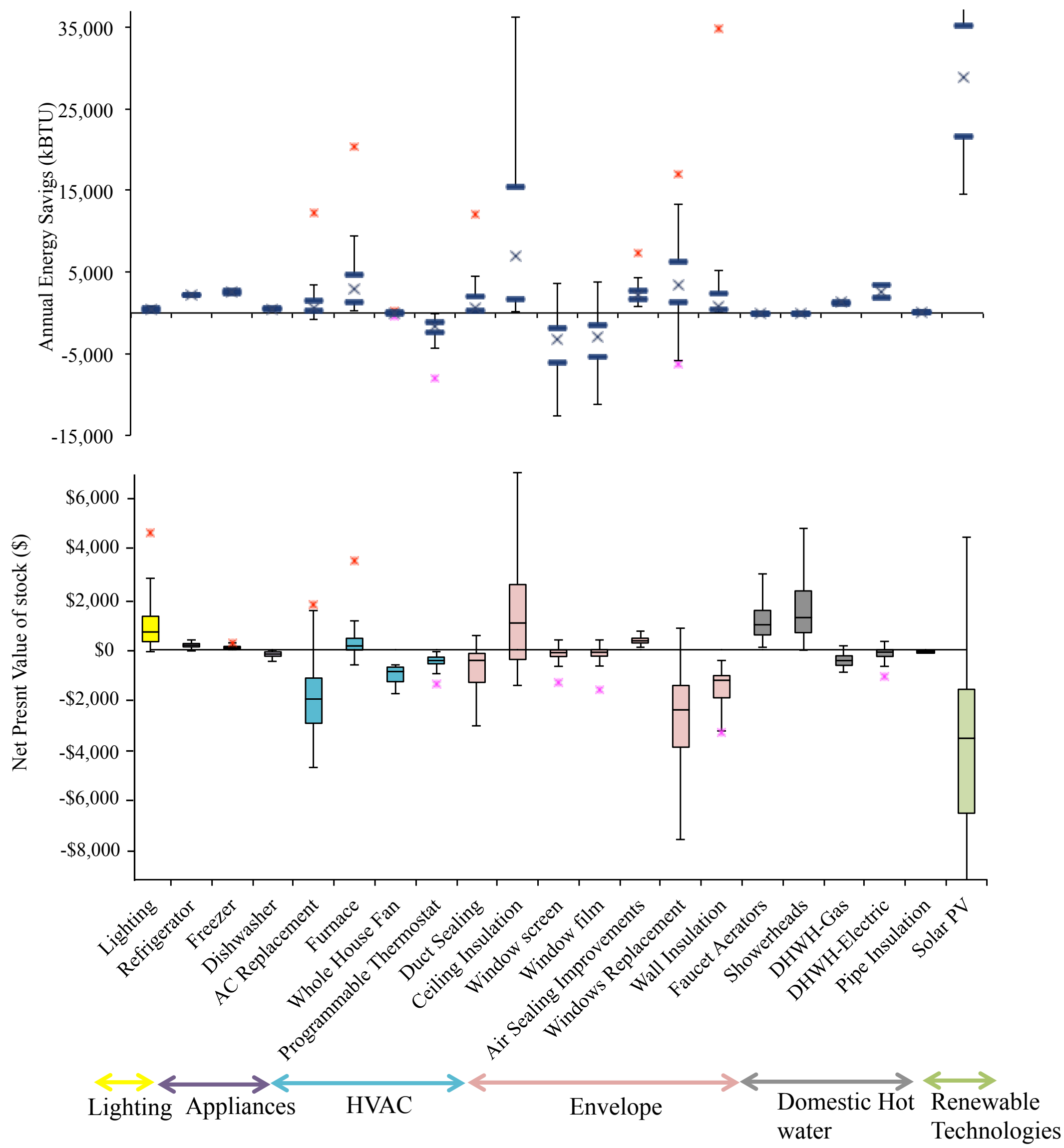


Figure 22: Distribution of annual energy savings from energy and water retrofits, and net present value of the proposed stock.

(NPV includes monetary benefits from energy and water conservation. We only include solar PV technologies in the energy savings chart to compare the magnitude of potential energy reductions from the rest of the efficient stock.)

Figure 22 shows that the residential lighting, faucet aerators and low-flow showerheads are relatively affordable, with a positive net present value for all the population in our study sample. In addition, ceiling insulation practices are predicted to be cost-effective, generating, on average, almost 7,000 kBtu/year in energy reductions for each household.

Figure 22 further indicates that solar PV production could displace roughly 63% of the annual unit energy consumption. Excluding renewable technologies, the analysis results show that Ceiling insulation has the highest potential for energy reductions, representing almost 15% of the household annual energy use. Surprisingly, window films and screens are shown to increase the household's energy use by roughly 7% annually. Nevertheless, on average, the percentage energy reductions generated by introducing the proposed energy efficient technologies is estimated to correspond to 89% of the household annual energy consumption. Figure 23 shows the distribution of the portion of annual energy reduction compared to the baseline annual household energy use, for our study sample.

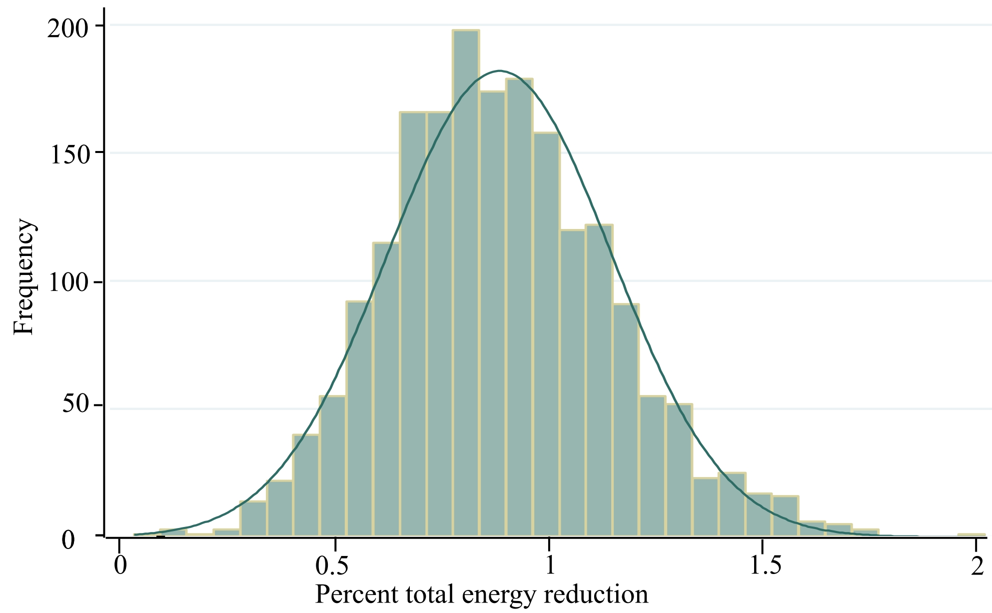


Figure 23: Distribution of total percentage energy reductions from the proposed efficient stock.

(I use the household's annual baseline energy use as the comparison values.)

4.5. Combining Retrofits and Rehabilitation

The modeling results of rehabilitation costs and retrofitting costs and benefits are integrated into a Monte Carlo simulation model to provide a clearer understanding of the capital share of rehabilitation and efficiency implementation practices, while controlling for uncertainties. The simulation results are given in Table 24.

Table 24: Distribution of Net Present Values for rehabilitation and retrofitting practices

	Present value Distribution			
	Average	**Standard Deviation**	**Low (30th)**	**High (70th)**
Present Value of Energy Benefits	$24,888	$5,342	$21,626	$27,856
Present Value of Water Benefits	$1,278	$739	$811	$1,521
Present Value of retrofit Costs	$41,617	$9,015	$35,939	$46,636
Net Present Value of retrofits per unit	$(8,614)	$5,574	$(11,131)	$(5,447)
Total rehabilitation Cost per unit	$(31,821)	$(17,806)	$(19,468)	$(44,922)

4.6. PROPERTY OWNER DECISION PROCESS

Finally, I investigate the potential outcomes generated from the decision-making process of a property owner by considering financial incentives to renovate and implement energy and water retrofits for existing, low-income multifamily rental buildings.

Private owners can decide to “opt-in”, which means they could accept financial incentives and guarantee the property’s maintenance and rent affordability for 20 to 30 years. In this case, the owner might choose to directly pay utility bills and thereby benefit from the energy and water saving features or the owner could choose to include the utility costs in the rent, thus transferring the energy and water benefits to the tenants.

On the other hand, the property owner might decide to “opt-out” of the HUD assistance and sell the property at its market value, and prepay the potential mortgage subsidies. Figure 24 illustrates the options that the owners of multi-family affordable properties could follow in their decision-making process.

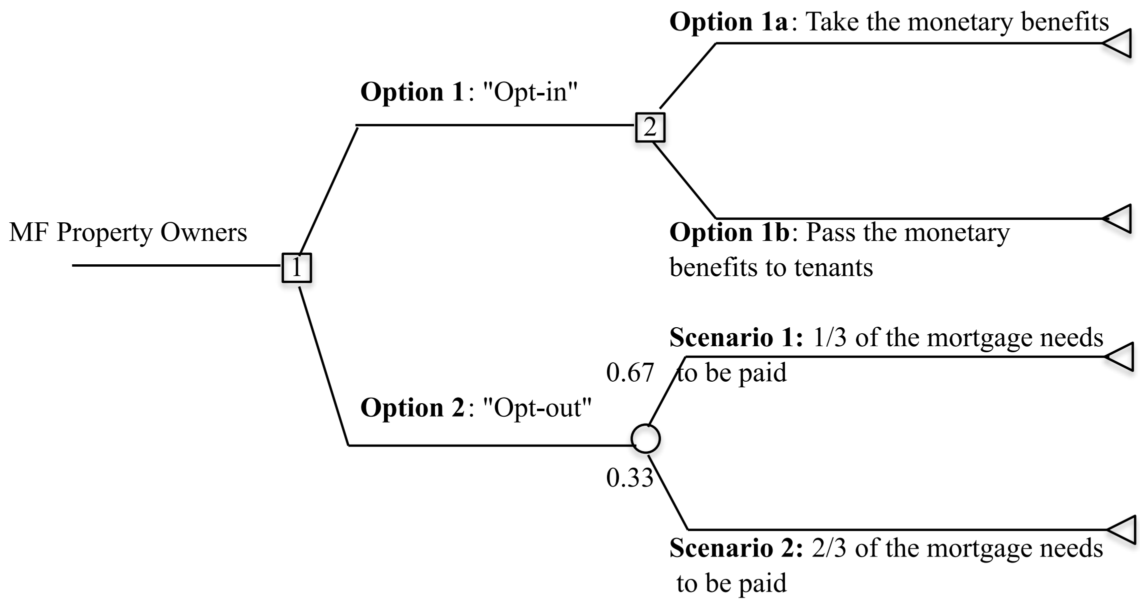


Figure 24: Decision-making tree describing the options that multi family property owners face

Option 1: Property owners could take the rehabilitation and retrofit incentives that the U.S. Department of Housing and Urban Development (HUD) offers, provided that the owner operates and maintains the property beyond a 20-year schedule of repairs and replacements. In this case, the property owner receives financial incentives and contributes with 20% to the rehabilitation and retrofit costs. I will refer to this option as "opting-in".

Furthermore, multifamily property owners who decide to "opt-in" could also decide to take the monetary benefits induced by the energy and water conservation measures (Option 1a) or to transfer those benefits to the tenants (Option 1b).

- *Option 1a:* The property owner can take the monetary benefits from energy and water retrofits if he pays the property utility costs (i.e. no sub-metering), which are usually included in the rent. He could, then, reasonably adjust the monthly rent values to incorporate the owner's contribution in the rehabilitation and retrofit costs, while maintaining the rent's affordability for low-income households.

A 50-unit property spends \$ 69,150 on energy and water annually (see Table 20). Based on the modeling results, the proposed energy and water retrofitting practices induce \$ 1,687 monetary savings per year per dwelling unit, resulting in roughly \$ 84,350 savings per annum, for the entire property. Therefore, the property owner would receive \$ 15,200 annually, from energy and water cost reductions.

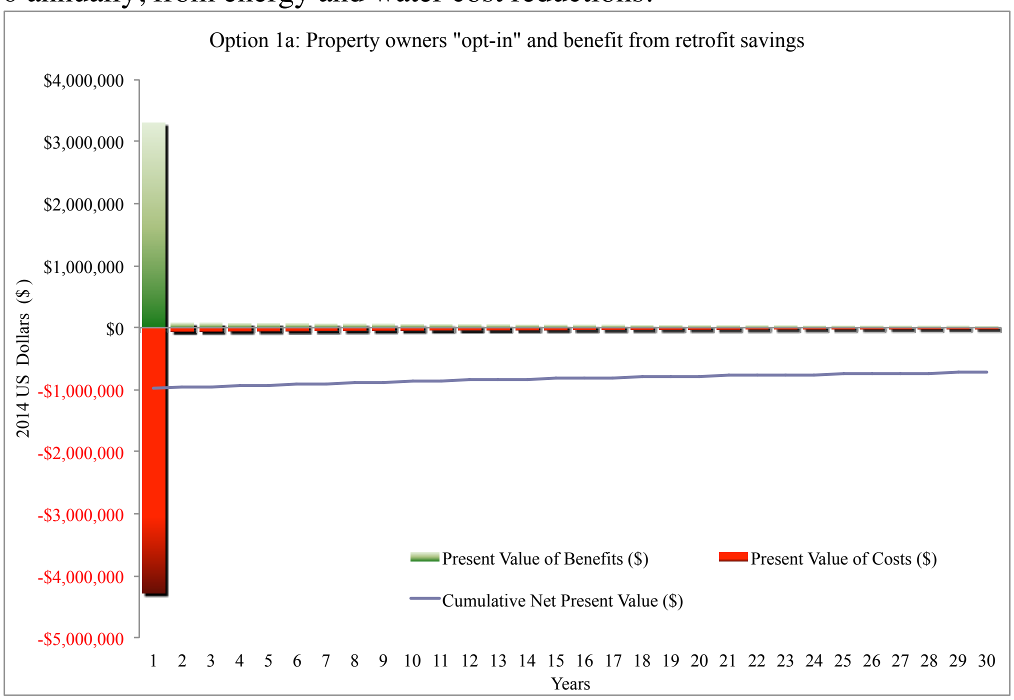


Figure 25: Cash flow diagram for Option 1a- Property owners "opt-in" and benefit from retrofit savings, for a 50-unit multi family building.

(The discount rate is assumed to be 4%, with a 30-year planning horizon.)

Figure 25 describes the cash flow for option 1a, where the owner of a 50-unit facility decides to take the HUD incentives and benefit from the monetary energy and water savings. The diagram shows the following present value components:

- Present Value of benefits $PV_{benefits}$ corresponds to the energy and water monetary savings and the HUD incentives in capital rehabilitation costs:

  $$PV_{benefits} = B_{savings} + Capital_{HUD}$$

  $$PV_{benefits} = \$\ 4.8\ M$$

- Present Value of costs PV_{costs} corresponds to the utility costs and the total costs of rehabilitation and retrofit:

  $$PV_{costs} = C_{utility} + Total\ Capital$$

  $$PV_{costs} = \$\ (5.4\ M)$$

Therefore, for the 30 years of operation and maintenance, the net present value of rehabilitation and retrofit for property owners who choose to take the monetary efficiency benefits is $ (581,000), which translates to an annual investment of roughly $671 per unit, that could be transferred to tenants through a $56-increase in the monthly rent. This reasonable raise in rent would enable the multi-family property to maintain its affordable status.

- *Option 1b:* The property owner can choose not to take the monetary benefits from energy and water retrofits if the tenants pay their own utility bills, through sub-metering. In this case, the owner could apply for additional subsidies or increase the monthly rent values to incorporate the owner's contribution in the rehabilitation and retrofit costs.

For a 50-unit property, Figure 26 illustrates a typical cash flow diagram if the owner chooses Option 1b.

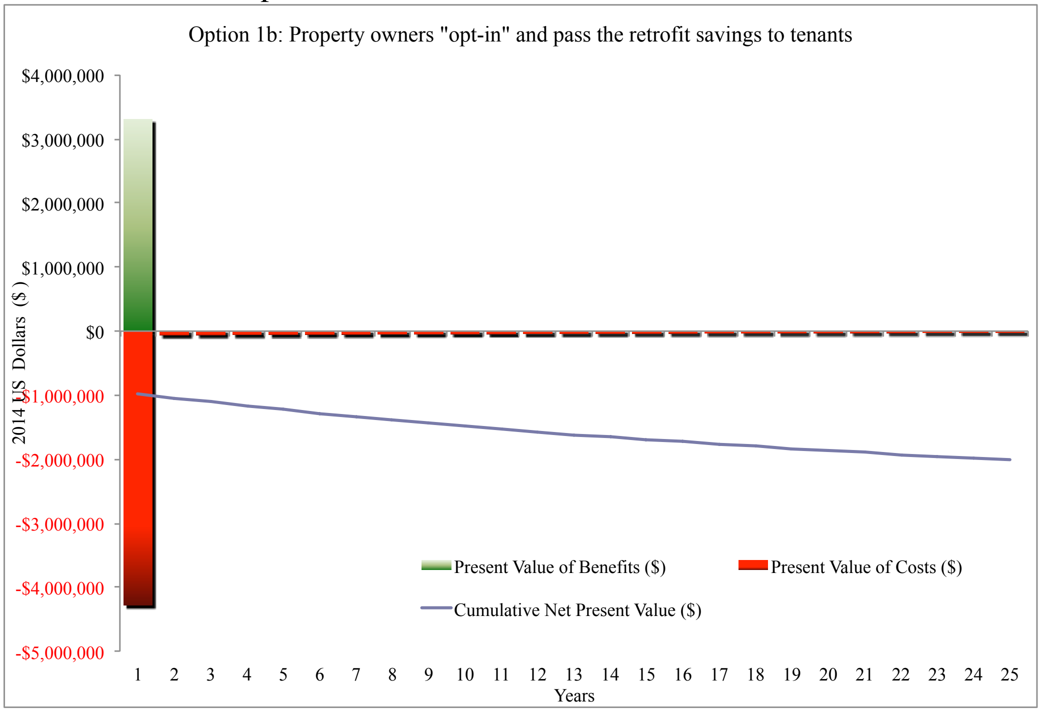


Figure 26: Cash flow diagram for Option 1b- Property owners "opt-in" and transfer the monetary benefits to tenants, for a 50-unit multi family building.

(The discount rate is assumed to be 4%, with a 30-year planning horizon.)

Figure 26 describes the cash flow for option 1b, where the owner of a 50-unit facility decides to take the HUD incentives and pass the monetary energy and water benefits to the renters. The diagram shows the following present value components:

- Present Value of benefits $PV_{benefits}$ corresponds solely to the HUD incentives in capital rehabilitation costs:

$$PV_{benefits} = Capital_{HUD}$$

$PV_{benefits} = \$\ 3.4M$

- Present Value of costs PV_{costs} corresponds to the utility costs and the total costs of rehabilitation and retrofit:

  $PV_{costs} \ = C_{utility} + \text{Total Capital}$

  $PV_{costs} \ = \$\ (\ 5.4M\ )$

Therefore, for the 30 years of operation and maintenance, the net present value of rehabilitation and retrofit for property owners who choose to pass monetary efficiency benefits to their tenants is $ (2M), which translates to an annual investment of roughly $2,360 per unit, that would be transferred to tenants through a $200-increase in the monthly rent. The property owner could also apply for other subsidies to avoid raising the rent and maintaining the property's affordable status.

Option 2: The private owner could "opt-out", sell the property and prepay the mortgage. To model this option, I consider two scenarios pertaining to the amount of mortgage that is left to be paid: one third and two thirds of the mortgage. I assume that the properties that still have 2/3 of the mortgage to be paid are less likely to opt-out of the HUD-assistance. Therefore, I assign a probability of 0.67 for scenario 1 and 0.33 for scenario 2 (see Figure 24). In addition, the property's selling price depends on the market condition. Therefore, I use a "selling multiplier" that is larger than 1 if the real estate market is propitious, and smaller than 0.9 if not. The owner's Net Profit is then computed as follows:

- $\text{Net Profit} \ = \ \text{Property Selling Price} - \text{Mortgage Payment}$

- $\text{Property Selling Price} = \text{Property Value} \times \text{Selling Multiplier}$

and $$\text{Mortgage Payment} = \underbrace{\mathrm{p}_1 \times \left(\tfrac{1}{3} \textit{Property Value}\right)}_{\text{Scenario 1}} + \underbrace{p_2 \left(\tfrac{2}{3} \textit{Property Value}\right)}_{\text{Scenario 2}}$$

where p_1 is the probability that the owner has to pay one third of the loan and p_2 is the probability that the owner has to pay two thirds of the loan (p_1=0.67 and p_2=0.33 as shown in Figure 24).

I use the "income approach" to estimate the value of the multifamily asset investment as they are considered income-producing assets owned by investors who seek a return on investment:

- $\text{Property Value} = {}^{\text{Net Operating Income}}/_{\mathrm{r}}$
- $\text{Net Operating Income} = \text{Gross Operating Income} - \text{Total Operating Expenses}$

where r is the capitalization rate (or return on investment) and the Net Operating Income is the net income (before mortgage payments) derived from operating the property. The following table illustrates how the Net Operating Income is calculated, for a 50-unit rental property:

Table 25: Input assumptions and calculation formulas to estimate the Net Operating Income for a 50-unit multifamily rental property.

Description	**Value assumption or calculation formula**
Gross Scheduled Rental Income (GSRI)	$= \text{Monthly Rent} \times 50 \times 12$
Vacancy & Credit Losses (VCL)	= $15,000
Gross Operating Income (GOI)	$= \boldsymbol{GSRI - VCL}$
Administrative Expenses	= $15,000
Leasing Expenses	= $15,000
Maintenance Expenses	= $30,000
Real Estate Taxes	= $50,000
Insurance	= $5,000
Utilities	= $64,650
Total Operating Expenses (TOE)	***= $179,650***
Net Operating Income	$= \mathbf{GOI - TOE}$

I model the uncertainties in the rent value and real estate market conditions using a Monte Carlo Simulation, based on the assumptions formulated in Table 26.

Table 26: Monte Carlo simulation variable assumptions for estimating the owner's Net Profit.

Input variable	Minimum value	Maximum value
Monthly rent	$ 500	$ 800
Selling multiplier in a "good" real estate market	1.2	2
Selling multiplier in a "bad" real estate market	0.01	0.9

Table 27 shows the Monte Carlo Simulation results for estimating the owner's net profit if the property is sold in "good" and "bad" real estate markets.

Table 27: Summary of the Monte Carlo simulation results to estimate the Net Profit from selling a 50-unit multifamily rental property, under a 6.5% capitalization rate.

	"Good Market"		*"Bad" Market*	
	Average	**St Deviation**	**Average**	**St Deviation**
Property Value	$3,002,332	$790,873	$3,002,332	$790,873
Remaining Mortgage	$1,328,899	$363,124	$1,328,899	$363,124
Selling Price	$4,805,509	$1,500,398	$1,380,388	$857,643
Net Profit	**$3,473,184**	**$1,202,591**	**$(29,577)**	**$793,151**

4.7. DISCUSSION

Nationwide, the US Department of Housing and Urban Development (HUD) assists multi-family properties by providing subsidized mortgage or other financial incentives to maintain their affordability for low-income families. However, these assisted properties are disappearing from the affordable housing stock as owners convert units to market-rate rentals or condominiums and because aging properties are lost to deterioration and default. In addition, the US public entities and private utilities still count upon energy efficiency and renewable resources to achieve the predicted social and environmental benefits, and increase consumer welfare. However, "measurement and verification" methods do not ensure that the monetary benefits resulting from DSM and renewables are not re-spent or eroded, possibly due to behavioral phenomena (e.g. "rebound effect"). Therefore, a reasonable way to utilize these benefits could be towards retrofitting low-income multi family housing units that might be displaced because of increasing costs of the real estate market. I, thus, develop replicable engineering economic models to estimate conventional rehabilitation, energy, and water retrofit costs with the goal of prioritizing policy interventions aimed at maintaining property location and use.

The analysis results suggest that energy and water conservation measures could displace nearly 89% of the household annual energy consumption annually and achieve roughly $1,700 monetary savings per unit and per annum. Water conservation measures, such as faucet aerators and low-flow showerheads, are estimated to be the most cost-effective retrofitting technologies, with a benefit/cost ratio exceeding 300%. In terms of energy efficiency, the highest energy reductions are mainly achieved by insulation practices, including ceiling and wall insulation, and air sealing improvements. However, while the energy produced by solar PV panels is expected to displace nearly 63% of the annual household energy use, the analysis results agree with the literature [Borenstein, 2008; Heal, 2009] and imply that the installation of solar PV is not cost-effective, with a net present value of -$4,500.

To maintain the affordability of multifamily rental properties and ensure the buildings safety, the U.S. Department of Housing and Urban Development (HUD) could assist the private owners by providing financial incentives that would partially cover the rehabilitation and retrofitting costs. This study estimates the capital investment needed to remodel these buildings to be roughly $ 43,000 per unit. Residents of the affordable multifamily units will probably benefit the most from the building retrofits that would also help avert future rent increases and counteract the high cost of energy and the financial burden it places on low-income households. As for the property owners, the energy and water retrofits could increase the property's market value by nearly $18,000 per unit, assuming a 6.5% capitalization rate.

A more thorough investigation of the decision-making process that faces the property owner shows that the owners who decide to "opt-in" and take the HUD's financial incentives can preserve the affordability of the rental units if they pay the utility costs and benefit from the retrofits monetary surplus. In this case, a reasonable increase in the monthly rent of $56 would ensure the profitability of the owner's investment. If the private owners operate their property through sub-metering, additional funding sources should be pursued to cover the remaining remodeling and retrofitting investment.

The property owner could also choose to "Opt-out" of the HUD's assistance and sell the building at the market value. This option is, however, subject to market uncertainties and rent rate variability. In fact, the owner's net profit from selling a 50-unit property could range from $1M to $5.8M (or $20,000 to $120,000 per unit) in a favorable real estate marker, but could also engender substantial losses up to $1.6M (or $33,000 per unit) if the housing market is not propitious. It is important to note that, in this case, the owner will loose the operating income generated from rent payments as well as the financial assistance provided by the housing authorities to maintain the multifamily houses affordable to low-income families.

5. Conclusions and Future Work

5.1. CONCLUSIONS AND CONTRIBUTIONS

The impact of demand-side management strategies (DSM) and renewable sources on energy demand has been, for a long time, a controversial issue in the research community. The U.S. government and private entities have invested tremendously in energy efficiency programs and solar technologies as a means to mitigate climate change repercussions and displace fossil fuel consumption. However, the performance of these measures in achieving expected energy reductions and controlling the environmental externalities remain uncertain. Using both empirical and engineering modeling techniques, this research provides unique insights on the potential outcomes of increasing DSM and residential solar technologies and their relationship with short-term households energy demand.

Section 2 presents a unique empirical analysis of the implications of marginal, joint technical change for multiple residential electricity end-uses on electricity consumption. This study is the first to quantitatively model the impact of multiple efficiency measures, as opposed to aggregate electricity consuming technologies, in order to better understand the observed performance of demand-side approaches on residential electricity use. It provides potential empirical evidence of the existence of rebound effects resulting from marginal technical changes within and across household end-uses, and challenges the existing assessments that disregard the technical state of multiple residential services in estimating the magnitude of rebound. Results indicate that the relative technical state of a home can significantly influence the performance of energy efficiency measures, particularly the presence of a programmable thermostat. Within space conditioning technologies, I generally find that sufficient technical improvement is needed to achieve energy savings, which could be due to engineering building performance or a declining marginal rebound effect as householders become thermally comfortable. The study results also demonstrate that the net effect of technical change in households is dependent on the extent to which consumers seek new and existing energy services.

Section 3 empirically evaluates the performance of residential distributed solar photovoltaic panels and provides a rich methodological framework to control for unobserved preferences that drive PV installation. The analysis results suggest that PV adopters consume roughly 30% more electricity than non-PV adopters, which could be used for other technologies and services. Results also demonstrate that consumers leverage energy gains from PV electricity generation toward enhanced physical comfort (i.e. more use of air conditioning technologies). This study results further imply that homeowners might "take back" nearly 24% of the annual electricity produced from PV, regardless of the panels power capacity. Consumers who choose to install solar panels might feel "morally licensed" to use part of the energy gains from PV adoptions. However, as concluded in the study results described in Section 2, sufficient and consistent technical improvements could lead to the desired energy reductions.

The contribution of this analysis emanate from the diversified modeling framework that was developed to control for the unobserved factors in the empirical assessment of consumer responses to solar PV adoption. This work raises attention to possible cognitive drivers that could partially erode the energy gains from PV production and empirically quantifies the magnitude of these offset savings.

The analyses described in Sections 2 and 3 serve as empirical evidence of the limitations of demand-side strategies and solar technologies in achieving the expected net energy savings. Nevertheless, it is essential to recognize that these measures have a potential to contribute to mitigating environmental externalities. From a pure neoclassical perspective, these technologies provide a “surplus.” I and others have demonstrated that some of this surplus is eroded in the single family housing sector. However, other organizational structures may be less prone to the behavioral, cognitive, or technical barriers hypothesized here. In Section 4, I provide an engineering economic framework for the rehabilitation and retrofitting of affordable multifamily rental housing, as an environmentally preferable solution to use the financial benefits from demand-side and renewable technologies. I develop replicable methodologies to estimate renovation, water and energy retrofitting costs, for properties in Texas, in order to encourage local and state housing authorities to financially assist the private property owners to maintain the houses location and affordability to low-income families.

This work serves as a decision-making tool that provides an insight on the capital needs and the possible outcomes of rehabilitation and retrofitting practices for both public entities and property owners. The analysis also provides guidance to the private owners on the options that should ensure the profitability of multifamily properties, while maintaining their current affordability for low-income households.

5.2. Policy Recommendation and Future Research

Based on the research results presented in this dissertation, I identified the following recommendation to policy makers, demand-side and renewables program administrators for more effective and sustainable planning and intervention practices:

(1) Design portfolios of efficiency and solar technology interventions to achieve desired energy reductions

Demand-side programs might bundle incentives to achieve "enough" efficiency gains that could overcome behavioral responses, as opposed to providing rebates for a single efficiency upgrade. For example, the analysis results presented in Section 2 indicate that sufficient technical improvements within space conditioning end-uses could reduce the possibility that consumers "take back" the energy gains from efficiency interventions, particularly for programmable thermostats, air conditioning units, insulation, and type of windows.

Utilities could also design "cross-technology" rebates by coupling renewable energy and energy efficiency interventions to ensure that consumer behavioral response to technology adoption does not offset its benefits, as suggested by the analysis results in Section 3.

(2) Customize households energy audits using the existing technical state of the homes

Energy efficiency programmers might consider customizing the energy audits aimed at assessing the existing technical state of the house. Results described in Section 2 show empirically that the effect of efficiency interventions for space conditioning is relative to the baseline technical performance of homes. Therefore, customized energy audits would inform program administrators on the order of efficiency interventions that should achieve the desired reduction goals. For example, the installation of multi-pane windows could considerably enhance the performance of the existing building insulation. If it is the case, the programmers do not need to prescribe additional insulation upgrades. However, houses with greater insulation R-values (pre-intervention) could still be recommended to install multi-pane windows, for improved efficiency performance.

(3) Couple education and outreach with financial incentives to overcome the potential behavioral uncertainties

Providing significant financial incentives might drive consumers to "overuse" the free energy gains generated from enhanced technical improvements and rooftop PV adoption, as shown in Section 3. Utilities and program administrators could raise consumer awareness of the technical limitations of solar technologies and educate them on how to effectively benefit from rebates without offsetting the environmental benefits of the incentivized demand-side products. Based on analysis results described in Section 3, the amount of energy "taken-back", possibly for other uses, is not dependent on the size of PV panels, which suggests that homeowners might have received some education on the limitations of their panels.

(4) Prioritize retrofitting interventions aimed at enhancing the shell thermal efficiency for multifamily properties

Local and state authorities could offer preferential loans or mortgage subsidies for multifamily low-income rental houses to encourage upgrading home insulation, as this measure shows to be cost effective, with the highest potential for energy reductions (see Section 4). In addition, retrofitting practices could be incentivized through regulatory policies such as enabling the tenants to receive rent rebates if the property owner does not comply with minimum efficiency standards.

(5) Design an effective compensation approach for solar production

I recommend that utilities reinforce an effective compensation structure for solar PV production, as a voluntary offering. These compensation programs would apply to a larger range of capacities to incentivize the homeowners to "sell" the produced energy and refrain them from taking back the solar gains for other on-site consumption. Feed-In Tariffs (FIT) are an example of schemas that could build a market less inclined to "take back" the electricity gains from rooftop PV.

"Feed-In Tariffs" (FIT) are a policy mechanism aimed at encouraging the expansion of renewable electricity technologies. A FIT program ensures that customers with FIT eligible electricity generating systems, such as rooftop PV panels, receive a monetary compensation for the electricity that they injected into the grid. The State of Texas does not have a regulated FIT structure for solar production. Austin Energy provides a program that applies to residential PV installations of 20 kW and that is similar to a FIT, but with important distinctions, namely that the tariff rate is not set for a contract term, and may be adjusted annually according to AE's calculated value of solar. The value of solar energy incorporates different value components such as its environmental, transmission and distribution mitigation value, in addition to the solar energy and value per se.

(6) Determine the optimal incentive levels for solar technologies to better control the unobserved cognitive limitations

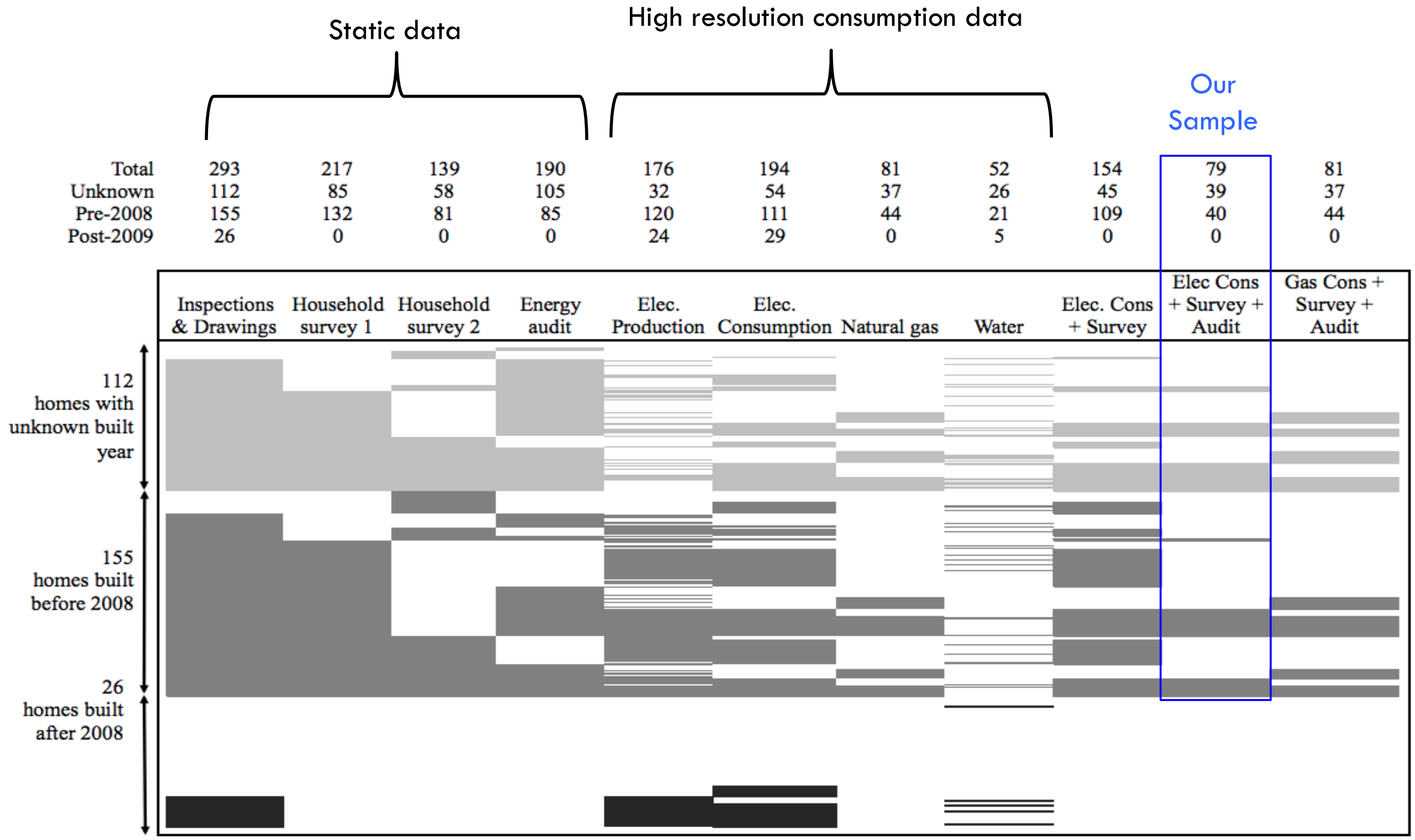
Substantial rebates on solar technology prices might drive consumers to "take back" part of the energy gains from solar electricity production. Consumers might perceive it as "free" electricity that they can use for other end-uses or services (as shown in Section 3). On the contrary, households that did not receive any financial incentives on purchasing solar panels might feel "morally licensed" to use more electricity because they paid the “full price” for their “environmentally conscious” action. Based on a “rational choice” theory, these consumers could feel that their investment would only be profitable if they increase their on-side consumption. Therefore, utilities should define the optimal rebate amounts that would drive PV installation rates but also offset the consumer’s “take-back” effect.

Furthermore, the research analyses described in this dissertation provide an opportunity to encourage further research. As the Demand-Side Management regulatory structure is disparate across the nation, future research studies could investigate the impact of voluntary actions and public private partnerships (PPP) on the residential energy demand. A nationwide study could be conducted across the U.S. states, comparing household responses to DSM programs in the strictest states such as California and New York to other more lenient regions like Arizona or Wyoming.

As for the renewable technologies, future analyses will explore the temporal shifts in energy demand and use that occur after adopting rooftop PV panels and the implication of financial rebates on PV adoption choice and performance. These analyses would involve iterative surveys and detailed interviews for households that participated in solar incentive programs to obtain higher level of resolution on consumer cognitive, decisional, and attitudinal factors. These inventories should be complemented with high-resolution and high-quality metered data on energy consumption, electricity provided by the grid, and electricity production for solar panels (similarly to the Pecan Street metered data).

Similarly to the methodological framework developed in Section 3, future studies with spatial variation would investigate the economic, technological, cognitive, and demographical factors that could drive the Electric Vehicle industry. These analyses would explore the variability in gas and electricity prices in different U.S. states, in addition to other household specific characteristics such as the number of conventional vehicles, the commute mileage, the occupancy, and the ownership of solar panels (as shown in Section 3) and assess their impact on electric vehicle ownership choice and energy performance.

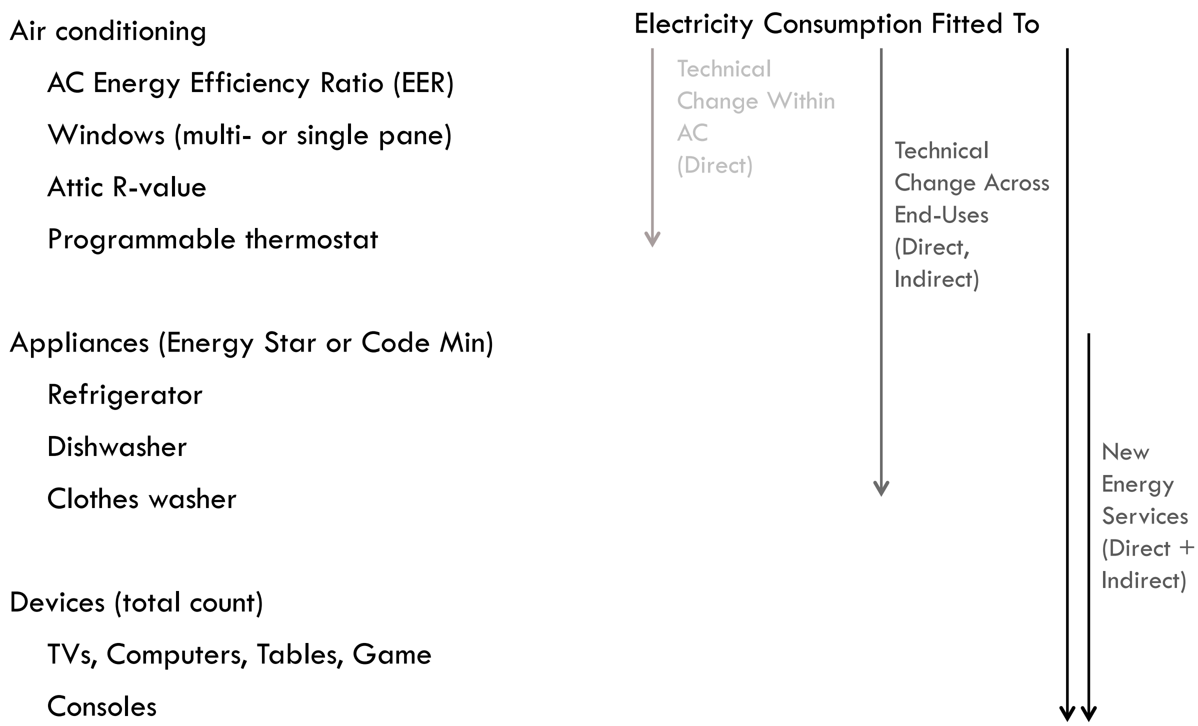
Appendix A: The Pecan Street Dataset Typology*



*This chart was realized by Pamela Torres a (PhD candidate at UT Austin), in association with Michael Blackhurst and Nour-El Imane Bouhou.

Appendix B: Supplemental Information-Section 2

SI-1: The Modeling Framework of Marginal Technical Change and Potential Implications on Residential Energy Demand:



SI-2: The Intraclass Correlation Coefficient (ICC)

To determine the ICC, we, first, built a "reduced mixed model" as shown in Equation SI-1. Excluding all variables that could explain part of the total variability in electricity consumption, we quantified the proportion of variability accounted for by the variation between houses.

$$\log(Y_{it}) = \beta_0 + R_i + \varepsilon_{it}$$

Equation SI-1

Where β_0 represents the model intercept, R_i represents Households' specific effects and ε_{it} represents the error terms.

SI-Table 1: "Reduced mixed model" results, based on Equation SI-1.

Explanatory variable	**Coefficient estimate**	**Standard Error**	**p-value**
Constant (bo)	6.59	0.0519	<0.0001

Standard Deviation Table:

Random effect		**Parameters estimate**	**Standard Error**	**95% confidence interval**
Household ID	$\sigma_{(households)}$	0.47	0.038	[0.401; 0.551]
	$\sigma_{(residuals)}$	0.431	0.00879	[0.414 ; 0.449]

Using the results in Table SI-1, we calculate ICC=$(0.47^2)/(0.47^2+0.431^2)$= 0.543.

SI-3: Results of mixed models for the statistically significant interactions

SI-Table 2: Regression mixed model for electricity consumption, with the interaction between Thermostat and windows performance, using the equation: $\log(Y_{it}) = \beta_0 + \beta_1 CDD_t + \beta_2 \frac{1}{\sqrt{House.Area_i}} + \beta_3 ProgTherm_i + \beta_4 Multipane_i + \beta_5 Devices_i + \boldsymbol{\beta_6 ProgTherm_i * Multipane_i} + R_i + \varepsilon_{it}$

Explanatory variable	Coefficient estimate	Standard Error	p-value
Constant (bo)	7.56	0.306	
Cooling Degree Days	0.00123	0.0000315	<0.0001
Floor Space (transformed to 1/(House Area))	-67.9	9.88	<0.0001
Programmable Thermostat	0.259	0.103	0.012
Multipane windows	-0.153	0.08	0.056
Devices	0.0186	0.00789	0.018
Programmable thermostat*Multipane windows	**0.43**	**0.156**	**0.006**

Standard Deviation Table:

Random effect		Parameters estimate	Standard Error	95% confidence interval
Household ID	$\sigma_{(households)}$	0.321	0.026	[0.274; 0.377]
	$\sigma_{(residuals)}$	0.278	0.00568	[0.267;0.289]

SI-Table 3: Regression mixed model for electricity consumption, with the interaction between Thermostat performance and air conditioning efficiency, using the equation: $\log(Y_{it}) = \beta_0 + \beta_1 CDD_t + \beta_2 \frac{1}{\sqrt{House.Area_i}} + \beta_3 ProgTherm_i + \beta_4 AC_i + \beta_5 Devices_i + \boldsymbol{\beta_6 ProgTherm_i * AC_i} + R_i + \varepsilon_{it}$

Explanatory variable	**Coefficient estimate**	**Standard Error**	**p-value**
Constant (bo)	8.34	0.467	
Cooling Degree Days	0.00127	0.0000365	<0.0001
Floor Space (transformed to 1/(House Area))	-65.7	9.94	<0.0001
Programmable Thermostat	0.645	0.367	0.078
AC Energy Efficiency	-0.0699	0.0328	0.033
Devices	0.016	0.00806	0.047
Programmable thermostat* AC Energy Efficiency	**0.0691**	**0.0337**	**0.04**

Standard Deviation Table:

Random effect		**Parameters estimate**	**Standard Error**	**95% confidence interval**
Household ID	$\sigma_{(households)}$	0.327	0.027	[0.278; 0.385]
	$\sigma_{(residuals)}$	0.32	0.00657	[0.307;0.333]

SI- Table 4: Regression mixed model for electricity consumption, with the interaction between Thermostat performance and Clothes washers, using the equation: $\log(Y_{it}) = \beta_0 + \beta_1 CDD_t + \beta_2 \frac{1}{\sqrt{House.Area_i}} + \beta_3 ProgTherm_i + \beta_4 ES.CWasher_i + \beta_5 Devices_i + \boldsymbol{\beta_6 ProgTherm_i * ES.CWasher_i} + R_i + \varepsilon_{it}$

Explanatory variable	**Coefficient estimate**	**Standard Error**	**p-value**
Constant (bo)	7.47	0.302	
Cooling Degree Days	0.00127	0.0000358	<0.0001
Floor Space (transformed to 1/(House Area))	-64.8	10.1	<0.0001
Programmable Thermostat	0.18	0.1	0.072
EnergyStar Clothes washer	-0.001835	0.0636	0.977
Devices	0.0162	0.00814	0.046
Programmable thermostat* EnergyStar Clothes washer	**0.293**	**0.168**	**0.04**

Standard Deviation Table:

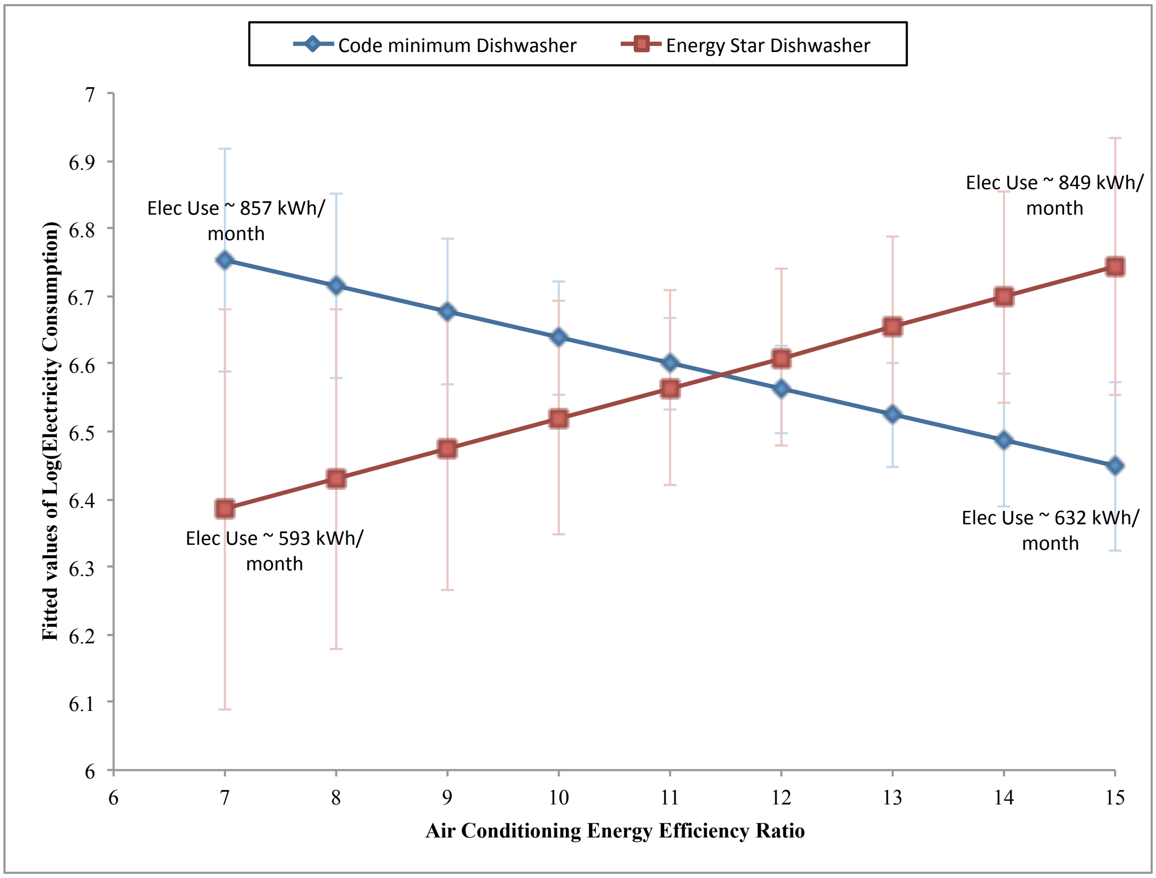
Random effect		**Parameters estimate**	**Standard Error**	**95% confidence interval**
Household ID	$\sigma_{(households)}$	0.331	0.0269	[0.282;0.389]
	$\sigma_{(residuals)}$	0.317	0.00645	[0.305; 0.33]

SI- Table 5: Regression mixed model for electricity consumption, with the interaction between Air Conditioning efficiency and Dishwashers, using the equation: $\log(Y_{it}) = \beta_0 + \beta_1 CDD_t + \beta_2 \frac{1}{\sqrt{House.Area_i}} + \beta_3 ProgTherm_i + \beta_4 \boldsymbol{AC_i} + \beta_5 ES\ DWasher_i + \beta_5 Devices_i + \boldsymbol{\beta_6 AC_i} * \boldsymbol{ES\ DWasher_i} + R_i + \varepsilon_{it}$

Explanatory variable	**Coefficient estimate**	**Standard Error**	**p-value**
Constant (bo)	8.16	0.374	
Cooling Degree Days	0.0013	0.0000321	<0.0001
Floor Space (transformed to 1/(House Area))	-69.5	9.86	<0.0001
Programmable Thermostat	0.0246	0.0797	0.758
EnergyStar Dishwasher	-0.947	0.425	0.026
AC Energy Efficiency Ratio	-0.0379	0.0196	0.053
Devices	0.0152	0.00801	0.058
AC Energy Efficiency Ratio * EnergyStar Dishwasher	**0.0828**	**0.0379**	**0.029**

Standard Deviation Table:

Random effect		**Parameters estimate**	**Standard Error**	**95% confidence interval**
Household ID	$\sigma_{(households)}$	0.326	0.0266	[0.278;0.383]
	$\sigma_{(residuals)}$	0.28	0.00578	[0.269;0.292]



SI-Figure 1: Fitted values of log (electricity consumption) for homes with varying AC and dishwasher efficiency (see SI-Table 5).

SI-Table 6: Regression mixed model for electricity consumption, with the interaction between Thermostat performance and Electric Vehicles, using the equation: $\log(Y_{it}) = \beta_0 + \beta_1 CDD_t + \beta_2 \frac{1}{\sqrt{House.Area_i}} + \beta_3 ProgTherm_i + \beta_4 Insulation_i + \beta_5 EV_i + \beta_5 Devices_i + \boldsymbol{\beta_6 ProgTherm_i * EV_i} + R_i + \varepsilon_{it}$

Explanatory variable	**Coefficient estimate**	**Standard Error**	**p-value**
Constant (bo)	7.61	0.294	
Cooling Degree Days	0.00129	0.0000315	<0.0001
Floor Space (transformed to 1/(House Area))	-67.1	9.88	<0.0001
Programmable Thermostat	0.0833	0.0778	0.284
Electric Vehicle	-0.0103	0.0602	0.865
Devices	0.0174	0.00807	0.031
Programmable thermostat* Electric Vehicle	**0.754**	**0.354**	**0.033**

Standard Deviation Table:

Random effect		**Parameters estimate**	**Standard Error**	**95% confidence interval**
Household ID	$\sigma_{(households)}$	0.33	0.0265	[0.282;0.387]
	$\sigma_{(residuals)}$	0.278	0.00567	[0.267;0.289]

SI- Table 7: Table summarizing the variables included in the 36 mixed models with interaction terms.

	Variables Included in the Mixed models with interaction terms										
Interaction	*CDD*	*Floor Space*	*T1* *ProgTherm*	*T2* *Multipane*	*T3* *Insulation R*	*T4* *AC EER*	*T5* *ES Clothes washer*	*T6* *ES Dishwasher*	*T7* *ES Refrigerator*	*T8* *Devices*	*T9* *Electric Vehicle*
T1*T2	X	X	X	X						X	
T1*T3	X	X	X		X					X	
T1*T4	X	X	X			X				X	
T1*T5	X	X	X				X			X	
T1*T6	X	X	X					X		X	
T1*T7	X	X	X						X	X	
T1*T8	X	X	X		X					X	
T1*T9	X	X	X							X	X
T2*T3	X	X	X	X	X					X	
T2*T4	X	X	X	X		X				X	
T2*T5	X	X	X	X			X			X	
T2*T6	X	X	X	X				X		X	
T2*T7	X	X	X	X					X	X	
T2*T8	X	X	X	X	X					X	
T2*T9	X	X	X	X						X	X
T3*T4	X	X	X		X	X				X	
T3*T5	X	X	X		X		X			X	
T3*T6	X	X	X		X			X		X	
T3*T7	X	X	X		X				X	X	
T3*T8	X	X	X		X					X	
T3*T9	X	X	X		X					X	X
T4*T5	X	X	X			X	X			X	
T4*T6	X	X	X			X		X		X	
T4*T7	X	X	X			X			X	X	
T4*T8	X	X	X			X				X	
T4*T9	X	X	X			X				X	X
T5*T6	X	X	X				X	X		X	
T5*T7	X	X	X				X		X	X	
T5*T8	X	X	X				X			X	
T5*T9	X	X	X				X			X	X
T6*T7	X	X	X					X	X	X	
T6*T8	X	X	X					X		X	
T6*T9	X	X	X					X		X	X
T7*T8	X	X	X						X	X	
T7*T9	X	X	X						X	X	
T8*T9	X	X	X						X	X	X

Appendix C: Supplemental Information-Section 3

SI-Table 1: Regression mixed model for monthly electricity use (see Equation 5)

Explanatory variable	Coefficient estimate	p-value	% change in consumption for 1 unit (or 10%$^{++}$) increase in X variable
Cooling Degree Days	0.001294 (0.0000315)	0**	0.129%
1/√(House Area)	-73.8 (11.6)	0**	8.15% $^{++}$
Insulation R value	-0.00562 (0.00287)	0.051*	-0.560%
Devices	0.0152652 (0.00831)	0.066*	1.54%
Programmable Thermostat	0.0898 (0.0791)	0.256	9.4%
Energy Star Clothes washer	0.0542 (0.0620)	0.382	5.57%
Photovoltaic panels (dummy)	**-0.05 (0.102)**	**0.625**	**-4.88%**
Constant	-0.00562 (0.373)	0**	-

** p-value<0.01 , * p-value<0.1, $^{+}$ p-value<0.2

Appendix D: Supplemental Information-Section 4

SI –Table 1: Regression results from the electricity demand model described by Equation 22 (electricity use is in BTU/year)

Variable	Coefficient Estimates	Std. Error	p-values
HDD	0.0000165	0.000014	0.239
CDD	0.0000666	0.0000219	0.002
Census Region:			
Midwest	0.1333573	0.0423053	0.002
South	0.149582	0.0479441	0.002
West	-0.0921546	0.0535888	0.086
Rental Structure:			
Rented	0.0758152	0.0388757	0.051
Occupied without payment of rent	0.252581	0.1265602	0.046
# Rooms	0.0657036	0.0124997	0
# Apartments per Floor	0.115548	0.0424334	0.007
Space heating equipment:			
Central Warm-Air Furnace	0.2178502	0.0486105	0
Heat Pump	0.1398887	0.0677148	0.039
Built-In Electric Units	0.2586899	0.0560376	0
Floor or Wall Pipeless Furnace	0.0337037	0.0876949	0.701
Built-In Room Heater	0.2511709	0.0943779	0.008
Fireplace	0.6635274	0.6159468	0.282
Portable Electric Heaters	0.1576545	0.1085081	0.146
Cooking Stove	0.5545377	0.436671	0.204
Other Equipment	-0.3800194	0.2229185	0.088
Main space heating fuel:			
Propane/LPG	0.2440918	0.2128797	0.252
Fuel Oil	0.0609456	0.0656164	0.353
Kerosene	-0.004571	0.3102995	0.988
Electricity	0.2998101	0.0394193	0
Wood	-0.4096177	0.4361814	0.348
District Steam	0.0556582	0.1069619	0.603
Age of main space heating equipment:			
2 to 4 years old	0.0620888	0.0543833	0.254
5 to 9 years old	0.0296596	0.050415	0.556
20 years or older	0.0806381	0.0493538	0.103
10 to 14 years old	0.040348	0.0516733	0.435
15 to 19 years old	0.1038562	0.05908	0.079

Fuel used by main water heater:			
Propane/LPG	0.005439	0.1354156	0.968
Fuel Oil	-0.0075938	0.0801636	0.925
Electricity	0.2226985	0.0345415	0
Solar	0.2746185	0.31227	0.379
Other Fuel	0.6066267	0.3763252	0.107
Air conditioning equipment:			
Window/wall units	-0.1457202	0.0439554	0.001
Both a central system and window/wall units	0.2379733	0.3079758	0.44
Log (Occupancy)	0.206007	0.0261899	0
Household age	0.0095579	0.0035019	0.006
Household age squared	-0.0001019	0.0000344	0.003
House Area (sq ft)	0.0001431	0.0000473	0.003
Vintage	0.0005118	0.0006536	0.434
# Floors	0.0053237	0.0033211	0.109
# Windows	0.0029745	0.001294	0.022
Constant	8.240035	0.1658048	0

SI –Table 2: Regression results from the natural gas demand model described by Equation 23 (natural gas use is in BTU/year)

Variable	Coefficient Estimates	Std.Error	p-values
HDD	0.0001579	0.0000184	0
CDD	0.0000795	0.0000408	0.052
Space heating equipment:			
Central Warm-Air Furnace	-0.2014354	0.0751984	0.008
Heat Pump	-0.2591354	0.1356159	0.056
Built-In Electric Units	-0.6287089	0.124966	0
Floor or Wall Pipeless Furnace	-0.3331629	0.1335771	0.013
Built-In Room Heater	-0.3197519	0.1313242	0.015
Fireplace	1.489014	0.8467192	0.079
Portable Electric Heaters	-0.1374924	0.2028408	0.498
Cooking Stove	-0.3296086	0.6016548	0.584
Other Equipment	-0.4903594	0.3537449	0.166
Main space heating fuel:			
Propane/LPG	-2.034975	0.6027769	0.001
Fuel Oil	-1.354022	0.1053134	0

Electricity	-0.8133708	0.0681827	0
Wood	-2.147507	0.5995224	0
District Steam	-1.393985	0.1663164	0
Age of main space heating equipment:			
2 to 4 years old	-0.0222005	0.1047366	0.832
5 to 9 years old	0.0604194	0.0948841	0.524
20 years or older	0.1355082	0.0935289	0.148
10 to 14 years old	-0.0494037	0.0988602	0.617
15 to 19 years old	0.0567212	0.1106496	0.608
Fuel used by main water heater			
Propane/LPG	-0.0019904	0.3520428	0.995
Fuel Oil	-0.7276513	0.1326278	0
Electricity	-0.6427011	0.0678349	0
Air conditioning equipment :			
Window/wall units	0.0303723	0.0721586	0.674
Both a central system and window/wall units	0.7587454	0.5957391	0.203
# Rooms	0.0333562	0.0228263	0.144
Log (Occupancy)	0.2396664	0.0475312	0
Household age	0.0138202	0.0065615	0.036
Household age squared	-0.0001188	0.0000635	0.062
House Area (sq ft)	0.0000719	0.0000815	0.378
# Floors	0.0130111	0.0049257	0.008
# Windows	0.0062177	0.0024141	0.01
Type of windows glass			
Double pane	-0.1096514	0.046694	0.019
Triple pane	-0.2214707	0.1938113	0.254
Constant	9.119046	0.2434238	0

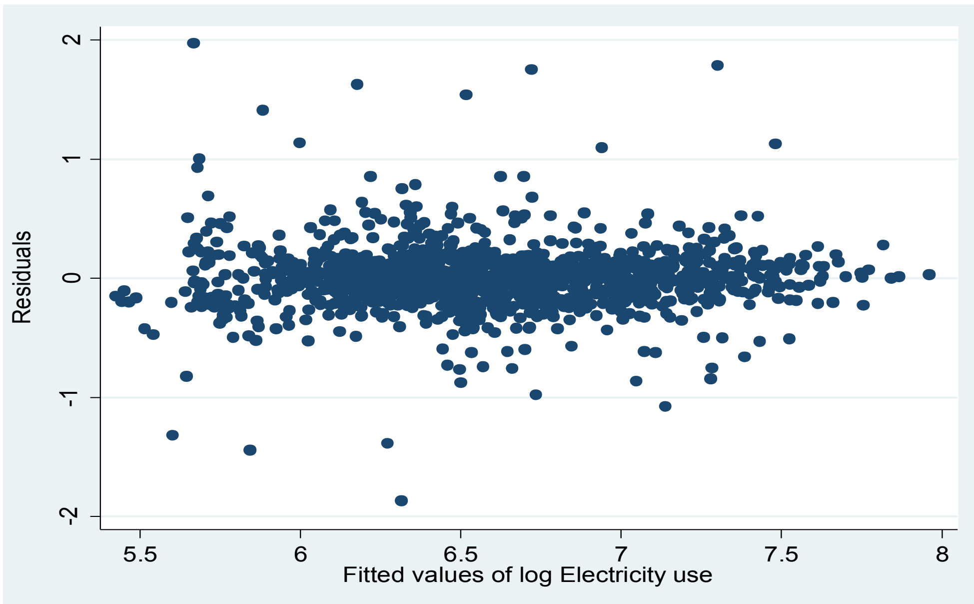
SI-Table 1: *RSMeans* historical cost index based on January 1st, 1993 = 100 as well as the computed value of an index based on January 1st, 2014 costs.

Year	Historical Cost Index Jan. 1, 1993 = 100		Current Index Based on Jan. 1, 2014 = 100		Year	Historical Cost Index Jan. 1, 1993 = 100	Current Index Based on Jan. 1, 2014 = 100		Year	Historical Cost Index Jan. 1, 1993 = 100	Current Index Based on Jan. 1, 2014 = 100	
	Est.	Actual	Est.	Actual		Actual	Est.	Actual		Actual	Est.	Actual
Oct 2014*					July 1999	117.6	58.0		July 1981	70.0	34.5	
July 2014*					1998	115.1	56.8		1980	62.9	31.0	
April 2014*					1997	112.8	55.6		1979	57.8	28.5	
Jan 2014*	202.7		100.0	100.0	1996	110.2	54.4		1978	53.5	26.4	
July 2013		201.2	99.3		1995	107.6	53.1		1977	49.5	24.4	
2012		194.6	96.0		1994	104.4	51.5		1976	46.9	23.1	
2011		191.2	94.3		1993	101.7	50.2		1975	44.8	22.1	
2010		183.5	90.5		1992	99.4	49.1		1974	41.4	20.4	
2009		180.1	88.9		1991	96.8	47.8		1973	37.7	18.6	
2008		180.4	89.0		1990	94.3	46.5		1972	34.8	17.2	
2007		169.4	83.6		1989	92.1	45.5		1971	32.1	15.8	
2006		162.0	79.9		1988	89.9	44.3		1970	28.7	14.2	
2005		151.6	74.8		1987	87.7	43.3		1969	26.9	13.3	
2004		143.7	70.9		1986	84.2	41.6		1968	24.9	12.3	
2003		132.0	65.1		1985	82.6	40.8		1967	23.5	11.6	
2002		128.7	63.5		1984	82.0	40.4		1966	22.7	11.2	
2001		125.1	61.7		1983	80.2	39.5		1965	21.7	10.7	
2000		120.9	59.6		1982	76.1	37.6		1964	21.2	10.5	

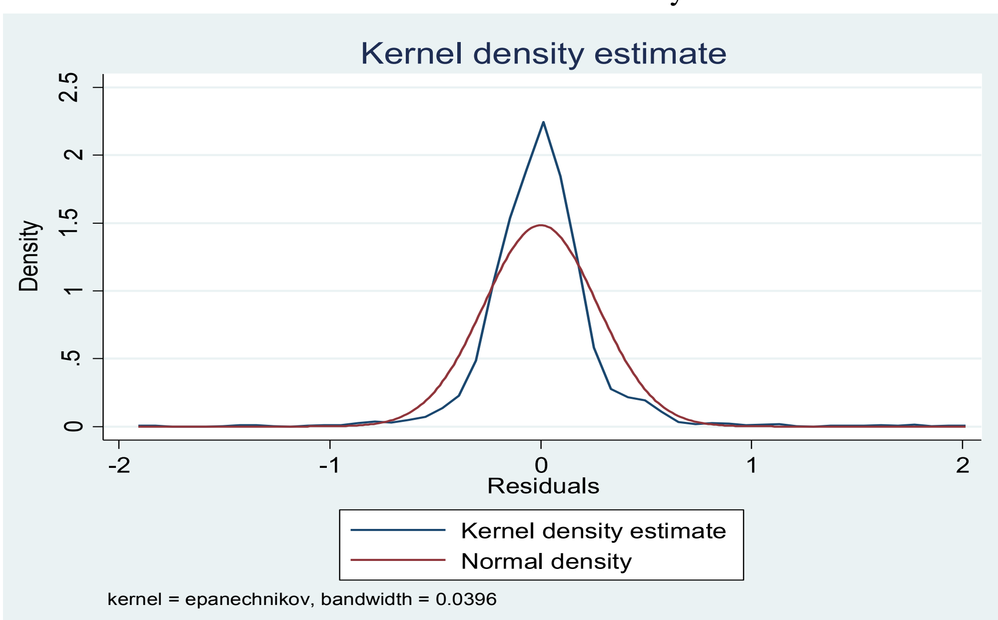
Appendix E: Examples of Regression Diagnostics for Sections 2, 3, and 4

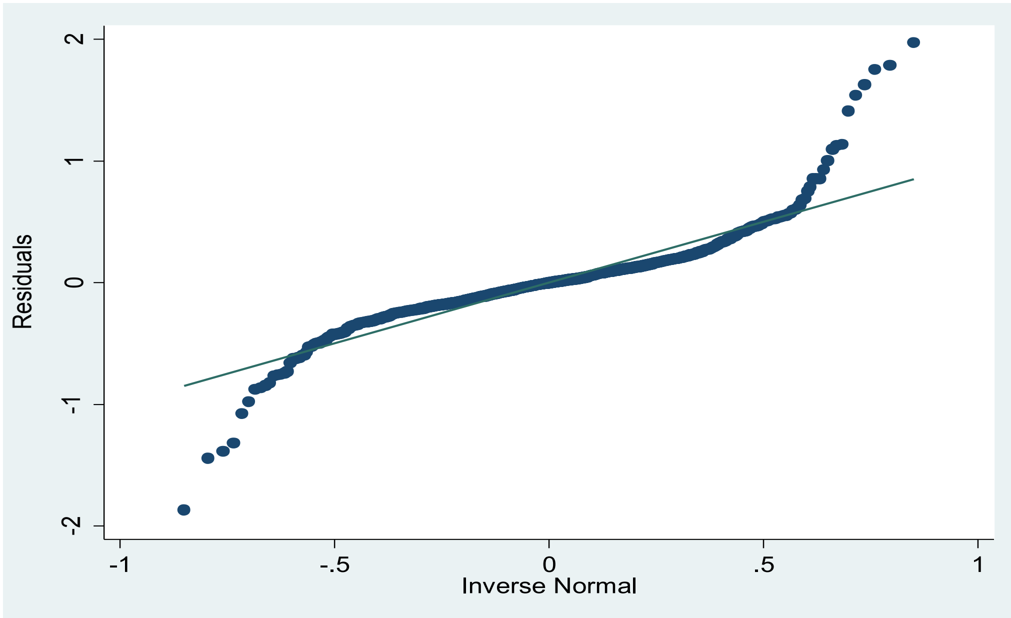
1) Regression Diagnostics of the mixed model of monthly electricity demand (Section 2-Equation 3):

- The error terms are independent, centered around zero

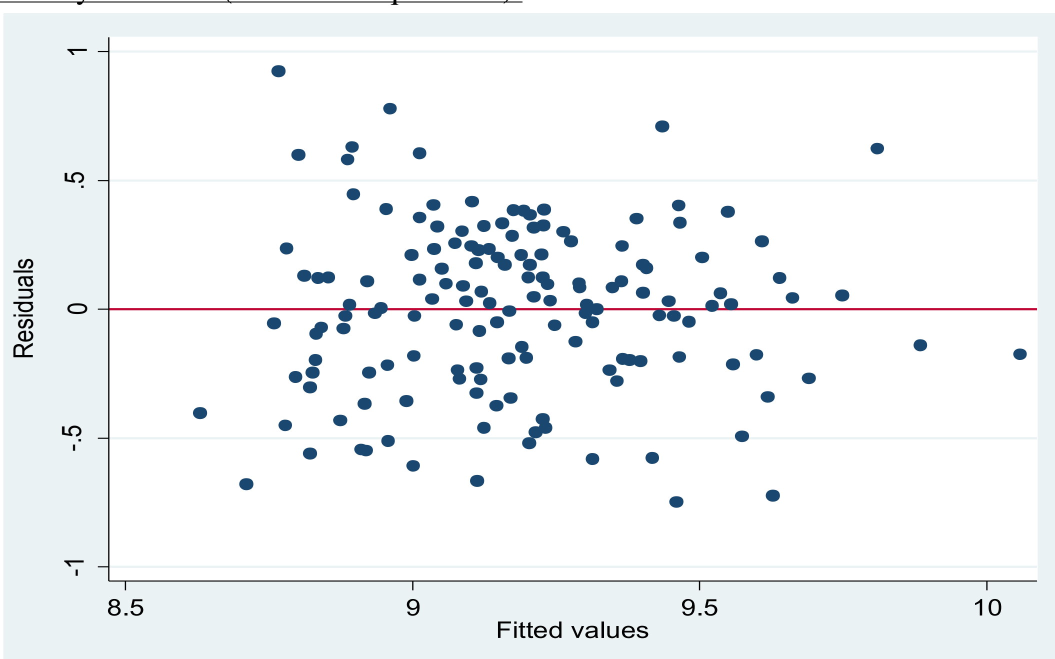


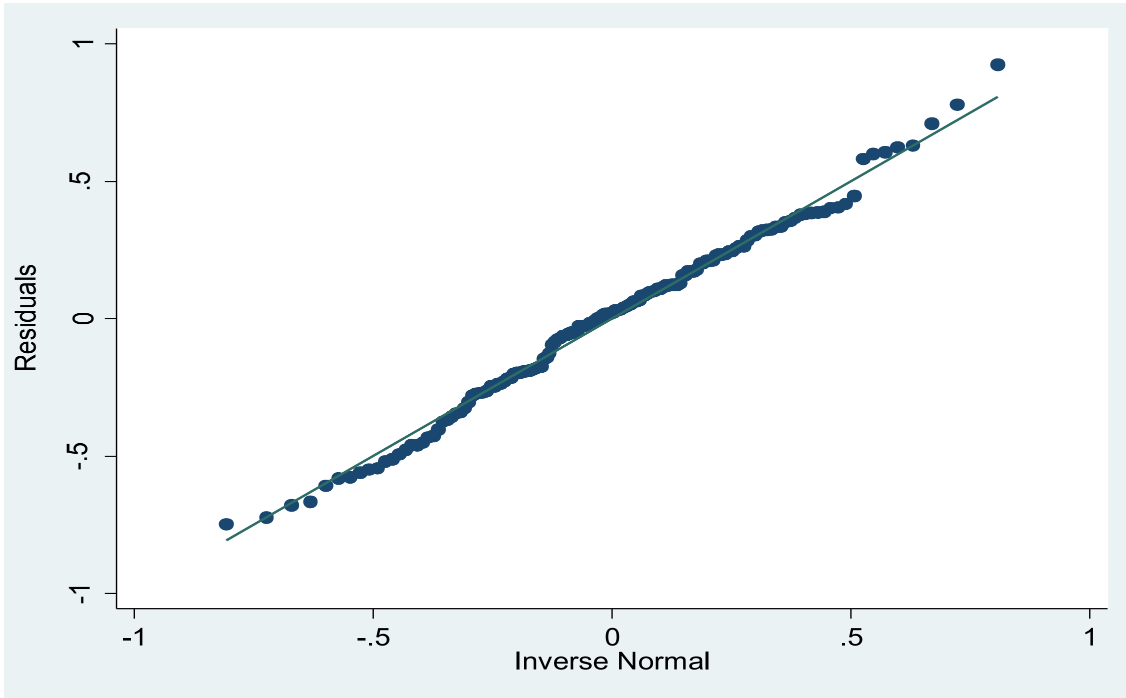
- The error terms are not skewed and close to normally distributed



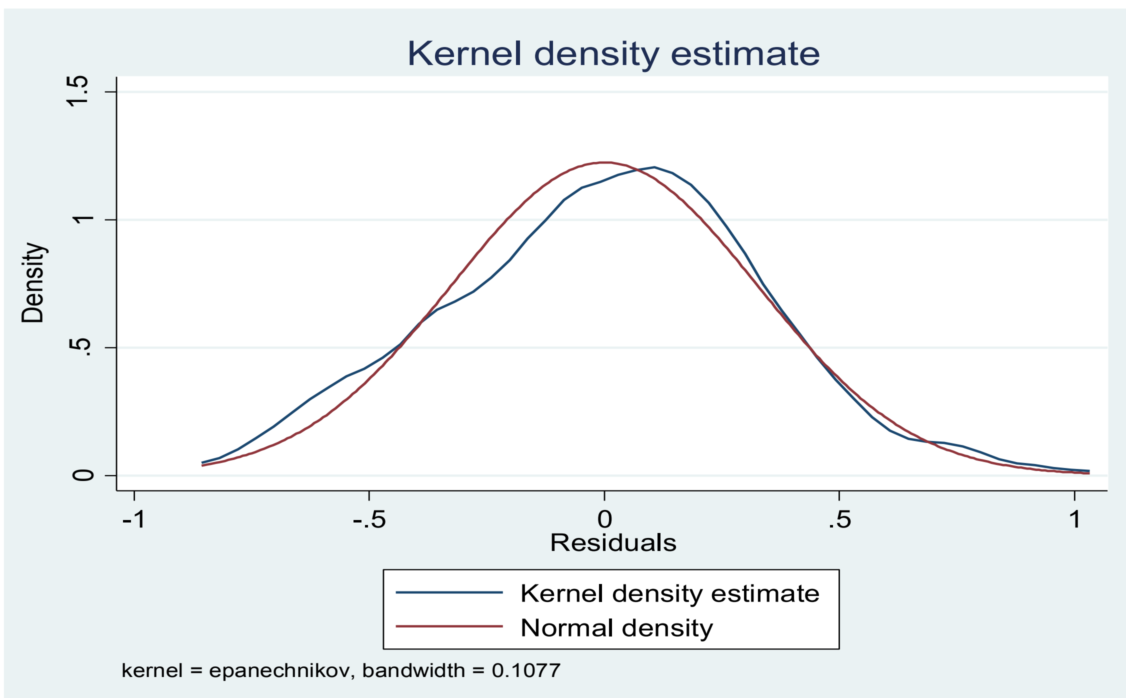


2) Regression Diagnostics of the annual electricity demand model with PV as a dummy indicator (Section 3-Equation 7):



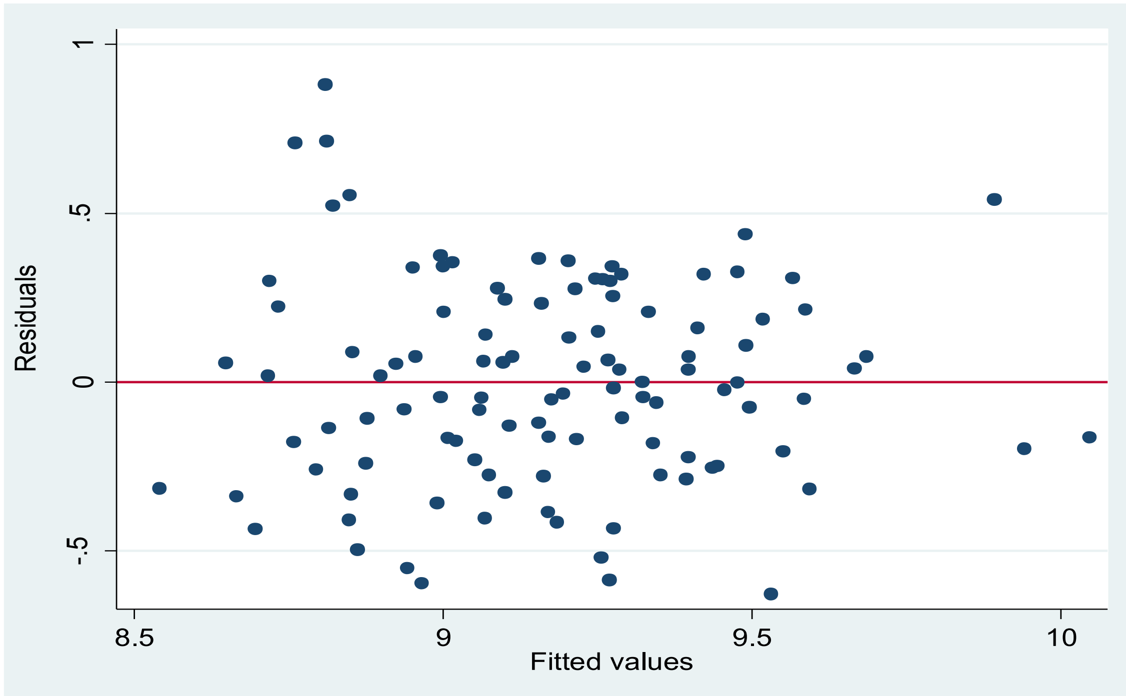


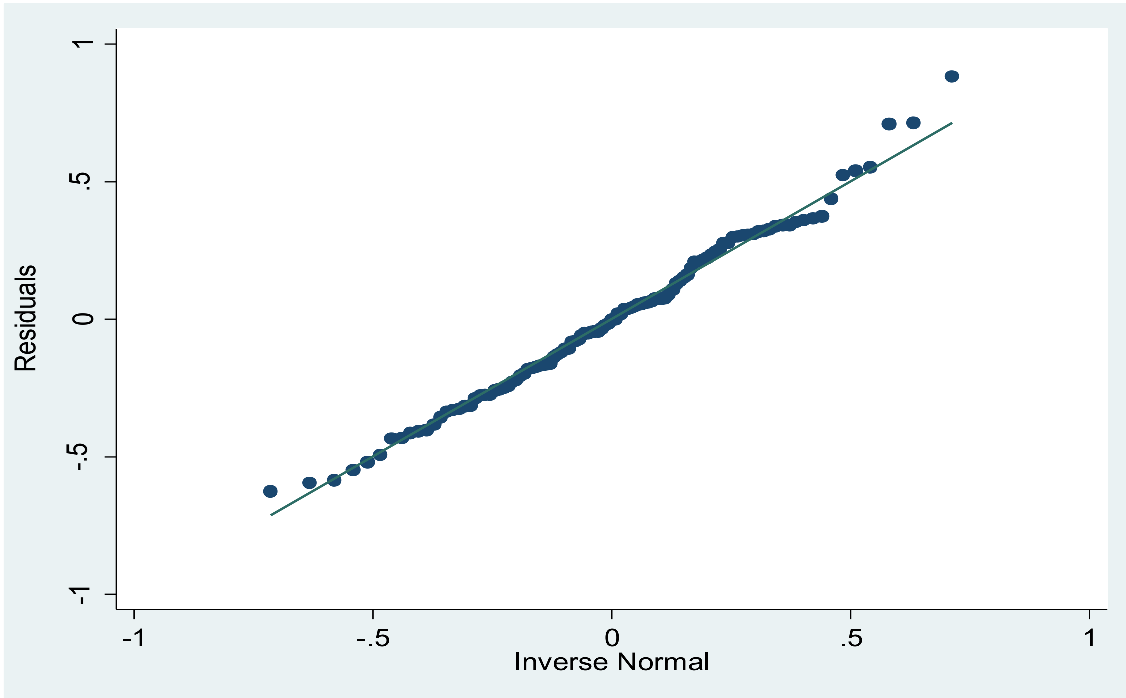
Residuals
1
.5
0
-.5
-1
-1
-.5
0
.5
1
Inverse Normal

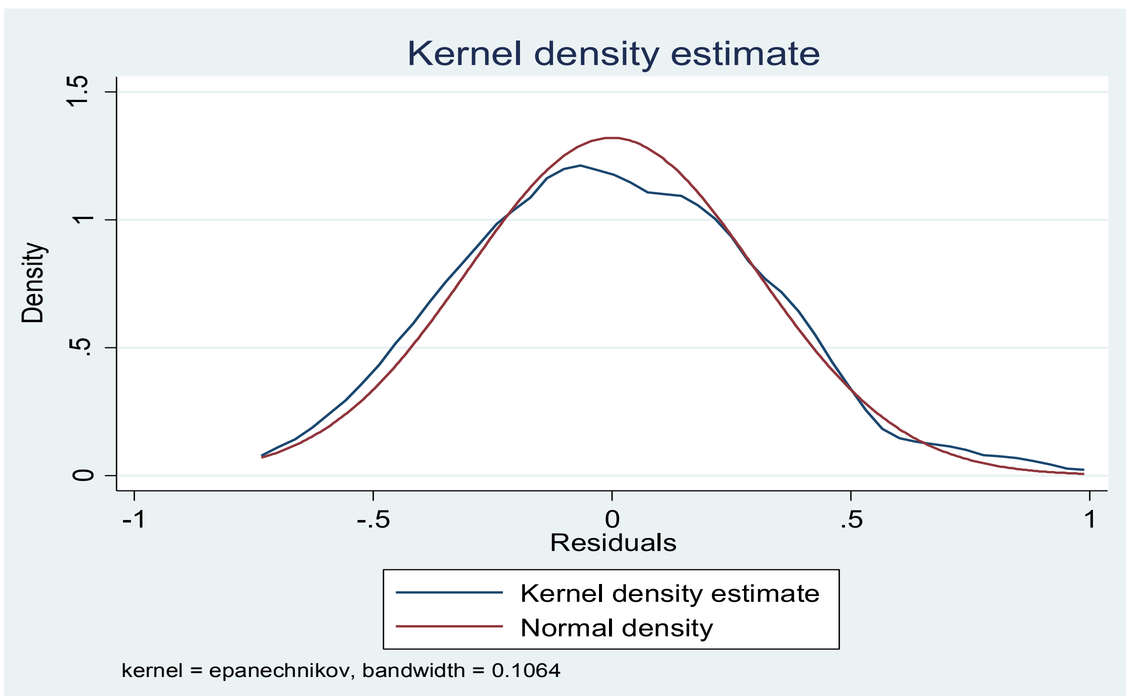


Kernel density estimate
Density
1.5
1
.5
0
-1
-.5
0
.5
1
Residuals
Kernel density estimate
Normal density
kernel = epanechnikov, bandwidth = 0.1077

3) <u>Regression Diagnostics of the annual electricity demand model using discrete choice modeling of PV adoption (Section 3-Equation 10):</u>




Residuals
Inverse Normal
-1
-.5
0
.5
1


Kernel density estimate
Density
Residuals
0
.5
1
1.5
-1
-.5
0
.5
1
Kernel density estimate
Normal density
kernel = epanechnikov, bandwidth = 0.1064

Appendix F: Monte Carlo Simulation Inputs Assumptions for Estimating Energy and Water Retrofitting Costs and Benefits

Measure	Variable	Unit	Low	High
Lighting	Capital Cost, Conventional	$	0.6	4
	Capital Cost, Efficient	$	3.8	6.8
	Electricity Savings	kWh/year	21.6	232.8
	Gas Savings	kBTU/year	0	0
	Water Savings	kGal/year	0	0
	Installation Labor Cost	$	0	0
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	1.05	2.95
	Units/apartment	unit	10	70
Refrigerator	Capital Cost, Conventional	$	426	694
	Capital Cost, Efficient	$	506	744
	Electricity Savings	kWh/year	617	650
	Gas Savings	kBTU/year	0	0
	WaterSavings	kGal/year	0	0
	Installation Labor Cost	$	107	109
	Current Market Share	%	100%	100%
	Service Life	years	15	18
	Units/apartment	unit	1	1
Freezer	Capital Cost, Conventional	$	195	465
	Capital Cost, Efficient	$	225	500
	Electricity Savings	kWh/year	670	825
	Gas Savings	kBTU/year	0	0
	Water Savings	kGal/year	0	0
	Installation Labor Cost	$	75	150
	Current Market Share	%	39%	46%
	Service Life	years	10	15
	Units/apartment	unit	0	1
Dishwasher	Capital Cost,	$	450	650

	Conventional			
	Capital Cost, Efficient	$	544	556
	Electricity Savings	kWh/year	87.3	180
	Gas Savings	kBTU/year	0	0
	Water Savings	kGal/year	0.36	0.4
	Installation Labor Cost	$	137.18	142.13
	Current Market Share	%	49%	80%
	Service Life	years	10	10
	Units/apartment	unit	0	1
AC replacement	Capital Cost, Conventional	$	813	1923
	Capital Cost, Efficient	$	1129	2894
	AC replacement	kWh/year	77	481
	Gas Savings, Efficient	kBTU/year	-184	24
	Installation Labor Cost	$	349	825
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	18	18
	Units/apartment	unit	1	1
Furnace	Capital Cost, Conventional	$	193	385
	Capital Cost, Efficient	$	406	910
	Electricity Savings, Efficient	kWh/year	0	0
	Gas Savings, Efficient	kBTU/year	1399	4603
	Installation Labor Cost	$	331	661
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	18	18
	Units/apartment	unit	1	1
Whole house fan	Capital Cost, Conventional	$	0	0
	Capital Cost, Efficient	$	410	725
	Electricity Savings, Efficient	kWh/year	-12	11
	Gas Savings, Efficient	kBTU/year	-47.5	-1
	Installation Labor Cost	$	302	535
	Current Market Share (efficient)	%	100%	100%

	Service Life	years	15	15
	Units/apartment	unit	1	1
Programmable Thermostat	Capital Cost, Conventional	$	39	48
	Capital Cost, Efficient	$	67	82.8
	Electricity Savings, Efficient	kWh/year	-195	18.8
	Gas Savings, Efficient	kBTU/year	-1998	-829
	Installation Labor Cost	$	20	25
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	12	12
	Units/apartment	unit	1	1
Duct Sealing	Capital Cost, Conventional	$	0	0
	Capital Cost, Efficient	$	16	32
	Electricity Savings, Efficient	kWh/year	9	91
	Gas Savings, Efficient	kBTU/year	202	1491
	Installation Labor Cost	$	88.3	178
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	18	18
	Units/apartment	unit	1	1
Ceiling Insulation	Capital Cost, Conventional	$	280.25	701
	Capital Cost, Efficient	$	359	872
	Electricity Savings, Efficient	kWh/year	35	356
	Gas Savings, Efficient	kBTU/year	1426	13384
	Installation Labor Cost	$	89	213
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	20	20
	Units/apartment	unit	1	1
Window Screen	Capital Cost, Conventional	$	0	0
	Capital Cost, Efficient	$	1	2
	Electricity Savings, Efficient	kWh/year	149	750

	Gas Savings, Efficient	kBTU/year	-8550	-3180
	Installation Labor Cost	$	1	2
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	10	10
	Units/apartment	unit	1	1
Window Film	Capital Cost, Conventional	$	0	0
	Capital Cost, Efficient	$	2	4
	Electricity Savings, Efficient	kWh/year	134	702
	Gas Savings, Efficient	kBTU/year	-7153	-2678
	Installation Labor Cost	$	1	2
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	10	10
	Units/apartment	unit	1	1
Air Sealing Improvements	Capital Cost, Conventional	$	0	0
	Capital Cost, Efficient	$	0	1
	Electricity Savings, Efficient	kWh/year	3	19
	Gas Savings, Efficient	kBTU/year	1631	2679
	Installation Labor Cost	$	0	0
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	12	15
	Units/apartment	unit	1	1
Window Replacement	Capital Cost, Conventional	$	2274	4268
	Capital Cost, Efficient	$	2324	4670
	Electricity Savings, Efficient	kWh/year	52	419
	Gas Savings, Efficient	kBTU/year	974	4831
	Installation Labor Cost	$	287	538
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	18	25
	Units/apartment	unit	1	1
Wall	Capital Cost,	$	289	565

Insulation	Conventional			
	Capital Cost, Efficient	$	270.5	1081
	Electricity Savings, Efficient	kWh/year	1	40
	Gas Savings, Efficient	kBTU/year	389	2232
	Installation Labor Cost	$	535.25	1257
	Current Market Share (efficient)	%	100%	100%
	Service Life	years	18	25
	Units/apartment	unit	1	1
Faucet aerators	Capital Cost, Conventional	$	0	0
	Capital Cost, Efficient	$	6.09	9.91
	Flow rate, Conventional	gpm	2.2	2.5
	Flow rate, Efficient	gpm	0.8	1.5
	Installation Labor Cost	$	0	0
	Current Market Share (efficient)	%	50%	100%
	Service Life	years	2	10
	Demand	minutes/hh/day	10	50
	Demand	minutes/hh/yr	3353	16763
	Units/apartment	unit	2	5
Showerheads	Capital Cost, Conventional Showerhead	$	5	5
	Capital Cost, Efficient, Showerhead	$	4.72	98
	Flow Rate, Conventional, Showerhead	gpm	2.5	2.5
	Flow Rate, Efficient, Showerhead	gpm	0.5	2
	Demand, shower length	minutes/shower	4	23
	Installation Labor Cost	$	0	0
	Current Market Share	%	68%	100%
	Demand, Shower Frequency	showers/hh/yr	365	1825

	Service Life	years	5	20
	Units/apartment	unit	1	3
Water Heater-NG	Capital Cost, Conventional	$	250	1500
	Capital Cost, Efficient	$	250	1500
	Electricity Savings factor	kWh/year/ GPY	0.0193	0.0263
	Gas Savings	kBTU/year	0	0
	Water Savings	kGal/year	0	0
	Installation Labor Cost	$	367	389
	Current Market Share	%	42%	80%
	Annual water consumption	GPY	14492	18864
	Service Life	years	10	25
	Bedrooms/apt	unit	1.23	2.16
	Units/apartment	unit	0	1
Water Heater-Electric	Capital Cost, Conventional	$	300	2880
	Capital Cost, Efficient	$	300	2880
	Electricity Savings factor	kWh/year/ GPY	0.0156	0.0767
	Gas Savings	kBTU/year	0	0
	Water Savings	kGal/year	0	0
	Installation Labor Cost	$	279	291.14
	Current Market Share	%	40%	80%
	Annual water consumption	GPY	14492	18864
	Service Life	years	13	25
	Bedrooms/apt	unit	1.2304068 03	2.1645703 66
	Units/apartment	unit	0	1
Pipe Insulation	Capital Cost, Conventional	$	0	0
	Capital Cost, Efficient	$	22	27.6
	Electricity Savings, Efficient	kWh/year	10	18
	Gas Savings, Efficient	kBTU/year	0	0
	Water Savings, Efficient	kGal/year	0	0
	Installation Labor Cost	$	61	106.5

	Current Market Share (efficient)	%	100%	100%
	Service Life	years	5	10
	Units/apartment	unit	1	1
Solar PV	Cost per Watts	$/Watt	2.75	5.75
	System size	kW	3	8
	Solar Radiation	$kWh/m^2/day$	4.94	5.99
	Utility incentives	$/Watt	1.1	1.8
	Current Market Share (efficient)	%	27%	91%
	Service Life	years	20	30
	Units/apartment	unit	1	1

Appendix G: Annual Energy Savings and Net Present Value estimates for Energy and Water Retrofits of Multifamily Affordable Housing

Measure	Annual Energy Savings (kBTU)		Net Present Value ($)	
	Media	*Standard Deviation*	*Median*	*Standard Deviation*
Lighting	444	201	$708	$818
Refrigerator	2160	32.5	$180	$89
Freezer	2545	153	$74	$58
Dishwasher	454	89.6	$(169)	$107
AC Replacement	656	126	$(1,958)	$1,103
Furnace	2849	288	$153	$488
Whole House Fan	-29	70.6	$(865)	$345
Programmable Thermostat	-1717	1236	$(428)	$210
Duct Sealing	637	479	$(422)	$1,391
Ceiling Insulation	6942	3456	$1,064	$1,956
Window screen	-3205	4237	$(116)	$312
Window film	-2840	4366	$(100)	$318
Air Sealing Improvements	2167	712	$356	$161
Windows Replacement	3428	2164	$(2,386)	$2,605
Wall Insulation	813	5430	$(1,212)	$744
Faucet Aerators	0	0	$993	$753

Showerheads	0	0	$1,280	$1,630
Domestic Water Heater -NG	1295	155	$(430)	$232
Domestic Water Heater - Electric	2638	972	$(95)	$226
Pipe Insulation	47	8	$(98)	$13
Solar PV	28885	7840	$(3,515)	$3,787

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